Innovation, Emissions Policy, and Competitive Advantage in the Diffusion of European Diesel Automobiles ⋆

Eugenio J. Miravete† María J. Moral‡ Jeff Thurk§

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Abstract

Volkswagen's recent admission that it knowingly deceived consumers and EPA regulators through a sophisticated scheme to mask emissions from its diesel vehicles resulted in significant financial penalties for the firm. We use this episode as motivation to assess the degree to which vehicle emissions policies impact the automobile industry, focusing on the European market where diesels are popular. Using Spanish automobile registration data, we estimate a discrete choice, oligopoly model of horizontally differentiated products. Our estimation uses changes in observed product characteristics to identify the underlying demand and cost parameters while allowing for correlation between observed and unobserved (to the researcher) product characteristics. We find the EU emissions policy promoted diesel vehicles by setting weaker thresholds for the emissions produced by these vehicles. Further, diesels amounted to an important competitive advantage for European auto makers over foreign imports. We conclude that the emissions policy employed by EU regulators amounted to a significant non-tariff trade policy equivalent to a 13 to 16% import tariff. Imposing product characteristic exogeneity in the estimation leads the researcher to over-state these effects.

Keywords: Trade Policy, Import Tariff Equivalence, Diesel Cars, Emission Standards.

JEL Codes: O33, L62, F13.

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† The University of Texas at Austin, Department of Economics, 2225 Speedway Stop 3100, Austin, Texas 78712-0301; Centre for Competition Policy/UEA; and CEPR, London, UK. Phone: 512-232-1718. Fax: 512-471-3510. E–mail: *miravete@eco.utexas.edu*; http://www.eugeniomiravete.com

‡ Facultad de Ciencias Económicas y Empresariales, UNED, Paseo Senda del Rey, 11, 28040, Madrid, Spain; and GRiEE, Vigo, Spain; Phone: +34-91-398-8930. Fax: +34-91-398-7821. E–mail: *mjmoral@cee.uned.es*; http://webs.uvigo.es/mjmoral

§ University of Notre Dame, Department of Economics, 919 Flanner Hall, Notre Dame, IN 46556. Phone: 574-631-3083. E–mail: *jthurk@nd.edu*; http://www.nd.edu/ jthurk/

1 Introduction

On September 18th, 2015 the United States Environmental Protection Agency (EPA) accused Volkswagen of devising a sophisticated scheme to deceive environmental authorities when testing for nitrogen oxide (NO_x) emissions. The notice of violation, and Volkswagen's subsequent admission, translated into an immediate 20% drop in the stock market value of VW shares due to concerns about the company's credibility as well as an estimated \$18 billion in fines. A likely outcome of this episode is the effective disappearance of diesel vehicles from the American market for a second time in two decades due to failure to meet emission standards.

We use the VW scandal as motivation to explore the implications of fuel emissions policy on the automobile industry. Rather than focus on the American market, we instead investigate the European market where diesels represent roughly half of all new car sales and the emissions policy chosen by regulators targets greenhouse gas emissions (CO, CO_2) but is lax on emissions connected to smog and acid rain (NO_x). As diesels produce little CO and CO_2 but a lot of NO_x, this policy appears to favor these vehicles. Our objective then is to assess whether European emissions policy drove the diesel's rise in Europe.

Using automobile registration data from Spain – a country which exhibited diesel adoption rates representative of Europe as a whole – we estimate a discrete choice oligopoly model similar to Berry, Levinsohn and Pakes (1995), henceforth *BLP*, to study an industry which is far from competitive and where products are horizontally differentiated. The *BLP* framework has become a workhorse model in the empirical Industrial Organization literature as it is flexible enough to generate reasonable substitution patterns between similar products while accounting for product characteristics known to consumers and firms but not to the researcher. For our purposes, the estimated model provides a laboratory to explore the equilibrium effects of more rigorous NO_x emissions policies which we model as an increase in the marginal costs of production required to reduce diesel NO_x emissions. We call these costs "retrofitting costs."

We find that diesels generated significant profits for European firms and the success of diesel vehicles in Europe was, in large part, the consequence of diesel-friendly emissions standards employed by European regulators. The model predicts that for even moderate levels of retrofitting costs firms maximize profits by increasing diesel prices and consumers respond by shifting consumption towards fuel-efficient gasoline engines produced by foreign auto makers. In other words, had the EU chosen a more rigorous NO_x standard, the popularity of diesels and the inherent competitive advantage they provided domestic auto makers would have decreased significantly, leading to an increase in imports from primarily Asian car manufacturers. Only by increasing the import tariff from 10.3% to between $13 - 16\%$ could EU regulators have pushed import penetration back to the level observed under the current EU emissions policy. This indicates the pro-diesel EU emissions policy amounted to a significant non-tariff trade policy as it had a disproportionately positive impact on those firms which had invested to offer diesels, namely domestic automakers.

A unique feature of our data set is that it captures the rapid consumer adoption of next generation diesel engines. Diesels were now significantly quieter, cleaner (*i.e.*, no black smoke), and more reliable than their predecessors while maintaining superior fuel efficiency and torque relative to comparable gasoline models. Our structural model then enables us attribute the diffusion of diesel vehicles to observable characteristics such as price and unobservable factors such as customers learning about these next generation diesel vehicles. Our estimates indicate that customer learning did play a role in the diffusion of diesels, therefore imposing more rigorous NO_x standards early in the diffusion of this innovation not only would have limited contemporaneous diesel sales but also would have decreased future demand for diesels. Further, we find this channel has large quantitative implications as it nearly doubles the equivalent import tariff implied by EU emissions policy (from 13% to 24%).

Researchers have historically focused on the role of explicit trade policies in shaping industries. An important example in the automobile industry is the voluntary export restraints placed on Japanese cars during the 1980s and early 1990s. Feenstra (1988) documents significant quality-upgrading by Japanese firms leading to the growth of luxury brands Acura, Infiniti, and Lexus in the US market. Berry, Levinsohn and Pakes (1999) show this policy increased profits for domestic firms and decreased welfare for domestic consumers while leaving significant tariff revenue on the table.

While the most popular tool to distort trade flows has been historically import tariffs, multilateral negotiations have largely driven these to zero. The result has been a growing empirical literature documenting the effects of trade liberalization on firm behavior. For example, Edmond, Midrigan and Xu (2015) evaluate the competitive effects of international trade on the Taiwanese electronics industry finding that foreign competition decreases misallocation and markups. Aw, Roberts and Xu (2011) find empirical evidence that international markets also provide incentive for firms to innovate.

Our results are important as they provide evidence that in a world with ever more free trade agreements, national policies such as environmental regulations can be effective tools to promote local manufacturers over competitive imports, *e.g.*, Ederington and Minier (2003) – perhaps our most original contribution. We also show that a non-tariff domestic policy which promotes the adoption of domestic innovations (or the development of innovations uniquely preferred by domestic consumers) can have a significant effect on trade by influencing demand broadly while tariffs just target price. This is a novel insight since such a policy may be welfare improving whereas tariffs are generally thought to be welfare decreasing.

To the best of our knowledge, this paper is the first application of an equilibrium model commonly used in empirical industrial organization to provide evidence of rent-seeking by countries using domestic policy. As such, it builds on the literature related to the interaction of domestic policy and international trade. The seminal theoretical contribution on this topic is Bhagwati and Ramaswami (1963) who address the substitutability between domestic policy and import tariffs. More recent works (*e.g.*, Staiger 1995, Bagwell and Staiger 2001, Deardorff 1996, Thurk 2014) take a more game theoretic approach and show that countries can use their domestic policies to extract rents from the rest-of-the-world leading to a suboptimal aggregate outcome.

To be clear, we are not making a statement about Pareto optimality nor are we claiming that European regulators designed their emission standards strategically to explicitly promote domestic auto makers. Rather, we argue that regardless of whether it was the intent of the policymaker or not, the effect of the environmental policy was to protect domestic European auto makers by encouraging a "home bias" for domestic consumers. We show our conclusions are robust to a variety of different assumptions and specifications but perhaps the most telling support are the EU Commission's own actions after Volkswagen announced it had also been cheating on *European* emissions policies since 2004. Rather than penalizing the firm with substantial fines or removing its cars from the European marketplace, EU regulators chose to increase the NO_x ceiling facing cars sold in Europe and committed to not revisiting the policy until 2019. We view this as evidence that the NO_x emissions policy employed in Europe was intimately related to the health of at least Volkswagen, if not all European auto makers.

Finally, the paper contributes to the current discussion on identification and estimation of *BLP* models by showing the practical repercussions of ignoring potential correlation between observable and unobservable product attributes. An important identification assumption used in a standard *BLP* estimation is that observable and unobservable product characteristics are uncorrelated. Given the paucity of observable characteristics – a common trait of *BLP* models – it seems plausible that unobservable characteristics are quantitatively important factors in determining consumer purchases as well as correlated with the observable characteristics either in the cross-section or across time. This is particularly true for us since diesels comprise a significant share of the market and many of the key features determining demand such as reliability, durability, and high torque at low r.p.m. are unobservable to econometricians but likely related to the observed weight or mileage as diesel vehicles are heavier and more fuel-efficient. Assuming exogeneity, therefore, may introduce quantitatively significant biases into the estimation and subsequent policy experiments – a hypothesis which we test.

Our estimation approach follows Petrin and Seo (2016) and allows for correlation between observable and unobservable automobile characteristics using the firms' first-order conditions for profit-maximization as moment conditions – an approach similar to Hansen and Singleton (1982). The idea is straightforward. Each period firms choose product attributes, observed or otherwise, to maximize profits. Though firms may have different beliefs or information regarding competitors' attribute choices, they all understand that their attribute choices influence equilibrium prices of automobile manufacturers through own and cross-price effects. The first-order conditions implied by the Bayes-Nash equilibrium provide moment conditions to estimate the structural demand and cost parameters. Intuitively, a firm's choice to make both larger (observable to us) and more reliable cars (unobservable to us) provides information about both consumer preferences and production costs for both attributes even though vehicle reliability, for example, can only be inferred by consumer purchases conditional on observable characteristics.

Perhaps not surprisingly, we do find significant correlation between the product characteristics we observe and the unobserved product characteristics needed to reconcile consumer purchases. We also find that our estimation approach yields demand estimates which are more elastic than employing a standard *BLP* estimation as well as more reasonable and significant point estimates – a similar finding to Petrin and Seo (2016). Ignoring the correlation between observable and unobservable product characteristics in the estimation would have led us to significantly over-state estimated markups and the profitability of diesels to European firms. The effect on the implicit import tariff is less stark, however, particularly for small retrofitting costs. We view this as both reinforcing our main results and providing some consolation that the bias introduced when a researcher estimates demand using the much simpler approach outlined in *BLP* may be small.

The paper is organized as follows. In section 2, we describe Volkswagen's introduction of the TDI innovation, its imitation by European auto makers, and summarize the main features of the Spanish market for diesel automobiles. In Section 3 we document differences in emissions policy between the US and EU; differences which materialized in the Volkswagen scandal. Section 4 describes the equilibrium model of discrete choice demand for horizontally differentiated products. Section 5 describes the estimation approach, discusses identification, and reports the estimation results in comparison to those implied by the standard *BLP* estimation strategy. In Section 6 use the estimated model to quantify the equilibrium implications of alternative emissions policy on the European automobile industry. In Section 7 we evaluate the implications to our results of assuming product exogeneity. Finally, Section 8 summarizes our results and contribution as well as discusses avenues for future research. Details of the estimation, additional results, data sources, and institutional details of the Spanish automobile market are documented in the Appendix.

2 The European Market for Diesel Automobiles in the 1990s

This section familiarizes the reader with the basic characteristics of the diesel technology; the institutional features of the European market that allowed for a swift take off of diesel sales in the early 1990s; and the evolution of the Spanish market.

2.1 A Significant Innovation - Next Generation Diesel Engines

In the late 19th century, Rudolf Diesel designed an internal combustion engine in which heavy fuel self-ignites after being injected into a cylinder where air has been compressed to a much higher degree than in gasoline engines. However, it was only in 1927, many years after Diesel's death, that the German company Bosch built the injection pump that made the development of the engine for trucks and automobiles possible. The first diesel vehicles sold commercially followed soon after: the 1933 Citroën Rosalie and the 1936 Mercedes-Benz 260D. Large passenger and commercial diesel vehicles were common in Europe from the late 1950s through the 1990s.

In 1989, Volkswagen introduced the TDI diesel engine in its Audi 100 model, a substantial improvement over the existing Perkins technology. A TDI engine uses a fuel injector that sprays fuel directly into the combustion chamber of each cylinder. The turbocharger increases the amount of air going into the cylinders and an intercooler lowers the temperature of the air in the turbo, thereby increasing the amount of fuel that can be injected and burned. Overall, TDI allows for greater engine performance while providing more torque at low r.p.m. than alternative gasoline engines. They are also credited with being more durable and reliable than gasoline engines although this was something yet to be learned by consumers at the time this technology was first introduced.[1] Following this major technological breakthrough, European manufacturers other than VOLKSWAGEN improved their diesel engines and European drivers enthusiastically embraced diesel automobiles. The incredible pace of adoption of diesel automobiles suggests that the TDI proved to be a significant technological advance and consumers gained little from waiting for additional incremental improvements, which have been few and of minor importance.[2]

2.2 Initial Market Conditions

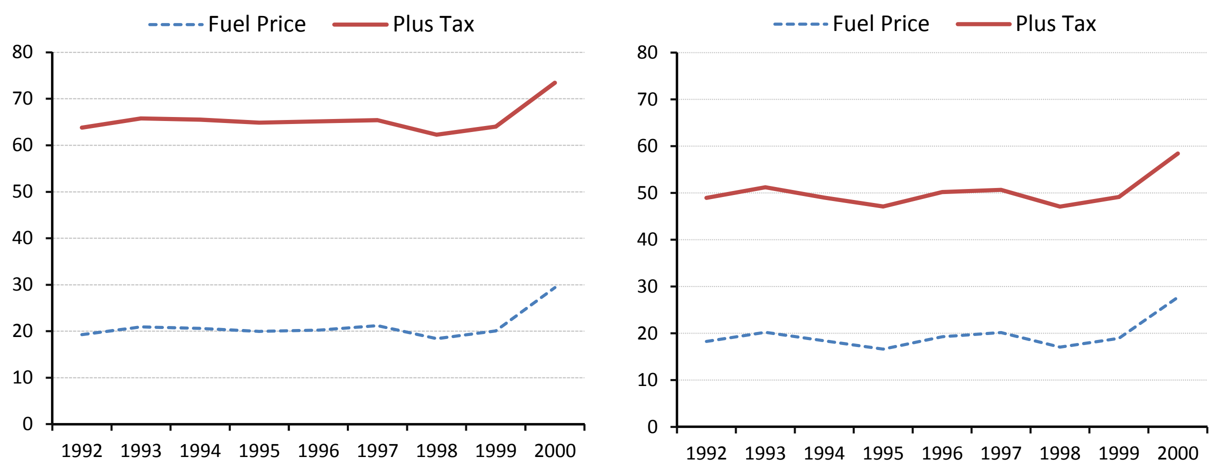
There are important institutional circumstances that helped build the initial conditions that were particularly favorable for the adoption of this new technology in Europe. The key element triggering

[1] See the 2004 report "Why Diesel?" from the European Association of Automobile Manufacturers (ACEA).

[2] This argument was first put forward by Schumpeter (1950, p.98) and later formalized by Balcer and Lippman (1984). More recently, it has been used by Manuelli and Seshadri (2014) to explain the half a century time span needed for the diffusion of the much studied case of tractors.

all these favorable development is the *European Fuel Tax Directive* of 1973. Following the first oil crisis of 1973, the then nine members of the European Economic Community gathered in Copenhagen in December of that year and agreed to develop a common energy policy. A main idea was to harmonize fuel taxation across countries so that drivers, and fossil fuel users in general, faced a single and consistent set of incentives to save energy. Coordination also limited the possibility of arbitrage across state lines as well as some countries free riding on the conservation efforts of other members. Fuel prices or their taxation were not harmonized overnight but the new Tax Directive offered principles of taxation that were eventually followed in every country. For the purposes of this study, the two most prominent features of this Directive are that fuels are taxed by volume rather than by their energetic content and that diesel fuel is taxed at a lower rate than gasoline. Figure 1 shows that in our sample diesel tax amounted to about 69% of gasoline tax (32 *vs.* 46 Euro cents per liter) resulting in systematically lower prices for diesel fuel.

Figure 1: Fuel Prices Gross and Net of Taxes (1994 Eurocents/liter)



(a) Gasoline (b) Diesel

Taxing fuels by volume offers a transparent criteria to monitor national policies. However, it also creates an incentive to use diesel fuel as diesel engines consume less per mile due to its higher energy content (129,500 BTU per gallon *vs.* gasoline's 114,000). The favorable tax treatment of diesel fuels exacerbated this effect. Historically, this approach was intended partly to help two economic industries particularly hit by the increase in oil prices: road transport and agriculture. With minor modifications, these principles have guided European fuel taxation until very recently. In 1997 the European Commission first suggested modifying these principles of taxation to reduce the differential treatment of diesel and gasoline fuels and incorporating elements of environmental impact of each type of fuel when setting taxes. It should be noted that this change in principles were only adopted in 2013. Thus, consumers faced stable and consistent incentives favoring diesel fuel consumption for a very long period of time.[3]

This favorable tax treatment of diesel fuel fostered the sale of diesel vehicles from the mid-1970s on. By the end of the 1980s, some large passenger cars and many commercial vehicles comprising almost 10% of the market ran on diesel fuel. Thus, when the TDI was first sold in 1989, Europeans, unlike Americans, were familiar with diesels and did not have a particularly negative perception of the quality of diesel vehicles.[4] More importantly, Europeans did not have to cope with the additional network costs commonly delaying the adoption of alternative fuels: by 1990 diesel pumps were ubiquitous, indeed available in every gas station, and it was easy to find mechanics trained to service these vehicles in case repairs were needed.

Initial conditions were thus more conducive to the success of the TDI technology than in any other automobile market in the world. And yet, it was not obvious that consumers were going to end up embracing this new technology when VOLKSWAGEN introduced the TDI engine. Diesels are known to achieve better mileage than otherwise identical gasoline vehicles, leading to future fuel cost savings, but they are also more expensive to purchase, presumably due to higher production costs or because manufacturers' attempt to capture consumer rents of drivers favoring diesel vehicles.[5] But since the diffusion of TDI coincided with a long period of historically low and stable fuel prices documented in Figure 1, the value of potential fuel savings were limited and so was the manufacturers' ability to overprice diesel automobiles.

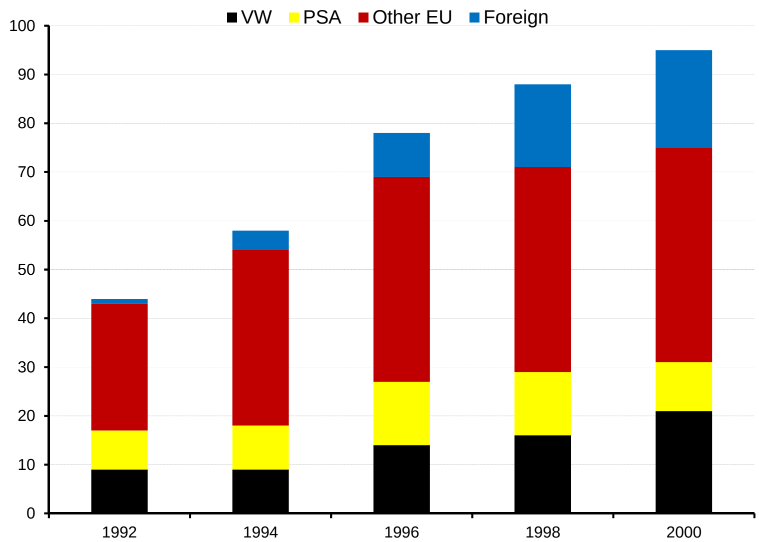
Figure 2 demonstrates that imitation of the TDI occurred quickly and was largely driven by rival European auto makers. This indicates the ineffectiveness of VOLKSWAGEN to protect its innovation via the patent system since it was not difficult for rival firms to offer their own improved diesel models in a relatively short period of time. This suggests a low cost of imitation – a trait which characterizes all "general technologies" (*e.g.*, Bresnahan 2010) – due to the fact the technology can be easily modified or reverse engineered. For consumers, imitation led to the introduction of more variety and better quality of vehicles to choose from while competition intensified in this market

[3] See `http://ec.europa.eu/taxation_customs/taxation/excise_duties/energy_products/legislation/index_en.htm` for a complete description of the European Fuel Tax Directive and its evolution over time.

[4] See `http://www.autosavant.com/2009/08/11/the-cars-that-killed-gm-the-oldsmobile-diesel/` for an account of how badly GM's retrofitted gasoline engines delivered poor performance when running on diesel fuel in the late 1970s and early 1980s and how such experience conformed the negative views of Americans on diesel vehicles for many years.

[5] Verboven (2002) studies the price premium paid for diesel vehicles relative to otherwise identical gasoline model and explains it as business strategy aimed to capture some of the rents of consumers with heterogeneous driving habits.

Figure 2: Number of Diesel Models Offered



segment, keeping diesel vehicles affordable, and therefore reinforcing the fast diffusion of this new technology.[6]

2.3 Evolution of Automobile Characteristics

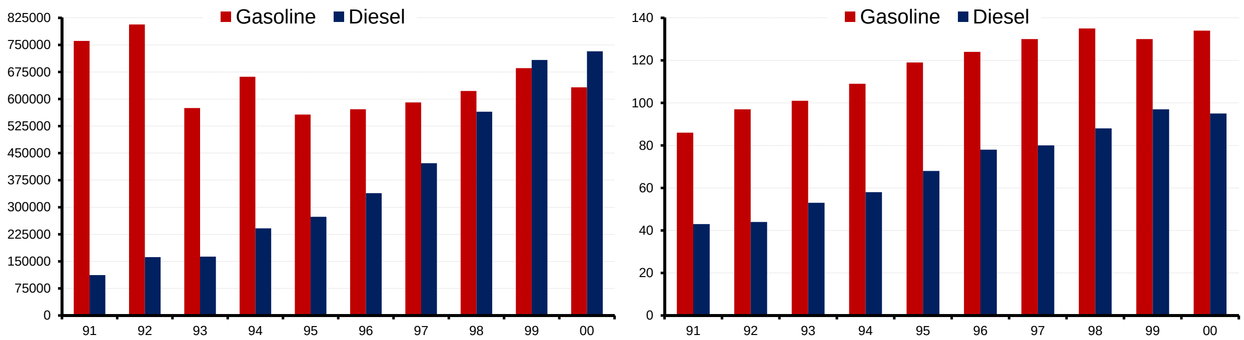
Our data include yearly car registrations by manufacturer, model, and fuel engine type in Spain between 1992 and 2000. After removing a few observations, mostly of luxury vehicles with extremely small market shares, our sample is an unbalanced panel comprising 99.2% of all car registrations in Spain during the 1990s.[7] Spain was the fifth largest automobile manufacturer in the world during the 1990s and also the fifth largest European automobile market by sales after Germany, France, the United Kingdom, and Italy. In our sample automobile sales range from 968,334 to 1,364,687 units sold annually.

Figure 3 documents the evolution and composition of sales in Spain during the 1990s. Figure 3(a) shows that sales of gasoline models were essentially identical in 1993 and 1995, about 573,000, despite a scrappage program in 1994, when they temporarily increased by 15%. Since then, sales of gasoline models increased at a steady pace until 1999 but they never reached the 1992 peak level again. The evolution of sales of diesel automobiles is starkly different. Initially in 1992, they only represented 16% of total sales but by the end of the decade diesels represented 54% of the

[6] VOLKSWAGEN was an important firm but not the leader in the Spanish market: RENAULT was by far the leader in the gasoline segment and PSA, which includes the French brands CITROËN and PEUGEOT, in diesel. See Figure A.1 in the Web Appendix.

[7] See Appendix A for further details.

Figure 3: Automobile Sales and Models by Year and Fuel Type



(a) Sales (thousands of vehicles) (b) Models Available

market, growing from 161,667 to 732,334 units sold in years 1992 and 2000, respectively. Moreover, diesel adoption in Spain mirrored that of other European countries.[8]

There was an equally impressive transformation of supply to meet this quick shift in demand. Figure 3(b) shows that by 1992, manufacturers already offered 44 diesels out of 141 models sold (although not all of them comparable to TDI). Such a large number of diesel models hints at automobile manufacturers fearing business stealing much more than the consequences of cannibalizing the sales of their own gasoline models. It also suggests that VOLKSWAGEN expected competitors to enter this segment when it decided to introduce the TDI technology. Furthermore, the number of models available grew significantly, both in the gasoline and the diesel segments, reflecting the effective entry of Asian manufacturers in the European market and a substantial increase in competition among fuel-efficient vehicles.[9] Since the entry of new models should reduce markups, consumers benefited from both an increase in variety and lower prices.

Table 1 summarizes the evolution of the features of vehicles sold in the Spanish automobile market during the 1990s.[10] By the end of the decade auto makers produced cars which were 36.1% more expensive, are 4.4% larger, and 11.6% less powerful (*i.e.*, HPW). The combined effect are cars that are 2.3% less fuel-efficient in terms of mileage and 2.8% less expensive to drive when we account for increasing fuel prices.

We document even more dramatic changes across gasoline and diesel models. While the prices of gasoline and diesel models both increased over the decade, the increase for gasoline

[8] See Figure A.2 in Appendix A.

[9] Asian imports include DAEWOO, HONDA, HYUNDAI, KIA, MAZDA, MITSUBISHI, NISSAN, SUZUKI, and TOYOTA. CHRYSLER is the only non-Asian imported brand. Thus, we use the terms "Asians" or "non-Europeans" when referring to imports. CHRYSLER sold its production facilities to PEUGEOT in 1978 and since then the few models sold in Europe are imported from the United States. On the contrary FORD and GM are considered European manufacturers. FORD has 12 manufacturing plants and has been continuously present in Europe since 1931. GM entered the European market in 1911, acquired the British brand Vauxhall and the German Opel in the 1920s and today operate 14 manufacturing facilities in Europe.

[10] Table A.2 in Appendix F.1 complements this description of product features reporting statistics by market segment.

Table 1: Car Model Characteristics by Origin and Engine Types

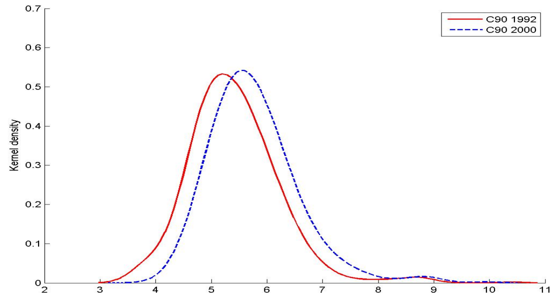
YEAR/GROUP	MODELS	SHARE	PRICE	C90	KPE	SIZE	HPW
1992							
EU: DIESEL	43	16.60	12.26	4.45	46.42	73.84	3.14
EU: GASOLINE	73	79.45	11.05	5.39	29.62	71.50	4.12
NON-EU: DIESEL	1	0.09	13.76	5.30	38.58	80.51	2.86
NON-EU: GASOLINE	24	3.86	14.88	5.82	27.31	77.99	4.53
ALL	141	100.00	11.40	5.25	32.33	72.15	3.97
2000							
EU: DIESEL	75	50.95	16.19	4.55	38.18	76.32	3.14
EU: GASOLINE	84	37.28	14.93	5.68	24.23	73.40	3.90
NON-EU: DIESEL	20	2.71	17.20	5.41	32.63	82.48	3.22
NON-EU: GASOLINE	50	9.06	13.66	6.11	22.80	75.32	4.08
ALL	229	100.00	15.52	5.13	31.43	75.31	3.51

Statistics weighted by relevant quantity sold. SHARE is the market share as defined by automobiles sold. PRICE is denominated in the equivalent of thousands of 1994 Euros and includes value added taxes and import tariffs. C90 is consumption (in liters) of fuel required to cover 100km at a constant speed of 90 km/hr. KPE is the distance, measured in kilometers, traveled per euro of fuel. SIZE is length×width measured in square feet. HPW is the performance ratio of horsepower per hundred pounds of weight.

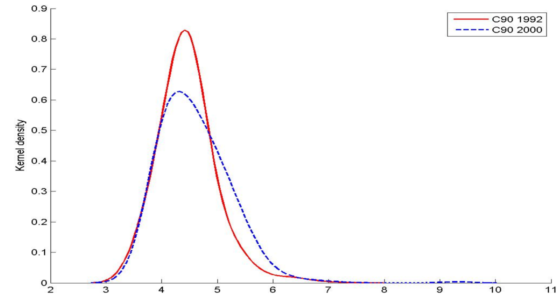
models was much larger (46.5% vs 27.7%). Interestingly, this coincided with the transformation of European production in just a few years: European vehicles represented 96% of sales at the beginning and 88% at the end of the 1990s. But while only less than one out of five European cars was a diesel in 1992, by year 2000 they sold four diesels for every three gasoline models. Overall, a quarter of a million fewer gasoline vehicles were sold by the end of decade while the production of diesel models increased by over half a million units, almost quadrupling production. Sales of diesel became so important in the market that non-European auto makers began introducing their own diesel models.

When deciding what type of engine to purchase, drivers compare observable product characteristics as well as likely related expected performance attributes of each engine, unobservable to econometricians. Since the difference between a diesel and gasoline version of a particular car model depends on only what's under the hood (*i.e.*, they share the same chassis), a consumer deciding between aa Audi A4 gas or diesel car bases her decision on differences in performance not car size. Specifically, diesel vehicles are about 10% heavier than similar gasoline versions; have 15% to 20% less horsepower than gasoline vehicles; and are between one and two thousand euros more expensive. Finally, diesel vehicles consume 20% − 40% less fuel than a comparable gasoline model, enabling a diesels to travel about 63% farther on a euro of fuel.

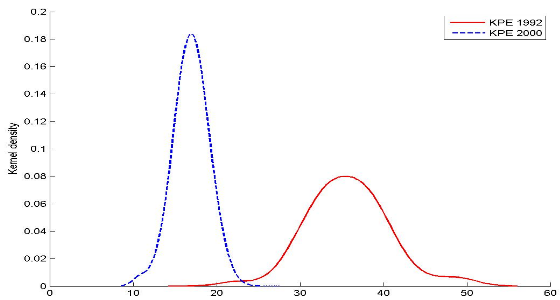
Figure 4: Change in the Distribution of Automobile Attributes



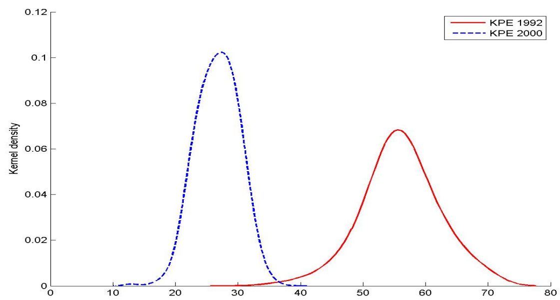
(a) Gasoline: Mileage (C90)



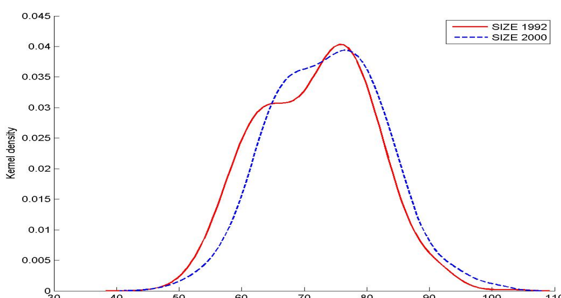
(b) Diesel: Mileage(C90)



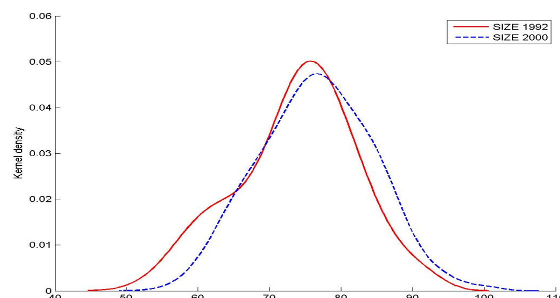
(c) Gasoline: Cost of Driving (KPE)



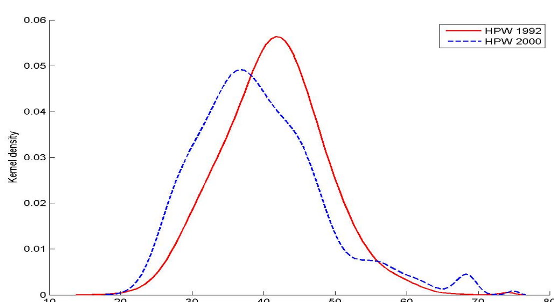
(d) Diesel: Cost of Driving (KPE)



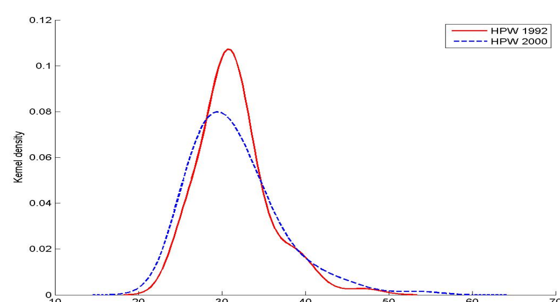
(e) Gasoline: SIZE



(f) Diesel: SIZE



(g) Gasoline: Performance (HPW)



(h) Diesel: Performance (HPW)

For diesels to succeed as they did, it is likely that this new technology was seen as desirable in many ways, and not only regarding fuel economy. The shift in the distributions of some observable automobile characteristics is shown in Figure 4 and formal tests of first and second order stochastic dominance are presented in Table F.1 in Appendix F.1. Despite the fact that all vehicles became larger, heavier and slightly more powerful during the decade, there is little evidence that gasoline vehicles differ much during the 1990s. Kolmogorov-Smirnov tests indicate that neither the early or late distribution of attributes of gasoline models dominate each other with the exception of KPE; the cost of driving gasoline vehicles is definitely higher by year 2000 (as a consequence of increasing fuel prices). Diesel vehicles on the other hand, show sign of substantial change during the decade; they are also more expensive to drive (KPE) by year 2000 despite the fact that they became more fuel-efficient (C90), as they are also larger (SIZE) and show weakly better performance (second order stochastic dominance in HPW). All this descriptive evidence hints at diesel vehicles becoming better products capable of increasingly attracting the interest of many drivers.

3 Vehicle Emissions Standards in the United States and Europe

Thus far we have documented the popularity of diesels among consumers (Figure 3) and discussed the significant imitation of diesels by largely European firms within a few years of Volkswagen's introduction of the TDI (Figure 2). And yet, despite how easy imitation appears to be, diesels almost disappeared in the U.S. during the same period of time. The common explanation for the different evolution of these two large markets attributes the success of diesels in Europe to the favorable tax treatment of the diesel fuels in Europe. This is a popular explanation that lacks empirical support, however. While it is true that reduced taxation of diesel fuel favors larger penetration of diesel vehicles in a cross-section of mature markets, *e.g.*, Grigolon, Reynaert and Verboven (2015), fifteen years of such policy only led to a 10% market share penetration by the early 1990s. This suggests that preferential diesel fuel taxes played a minor role in promoting diesel adoption prior to the TDI.[11]

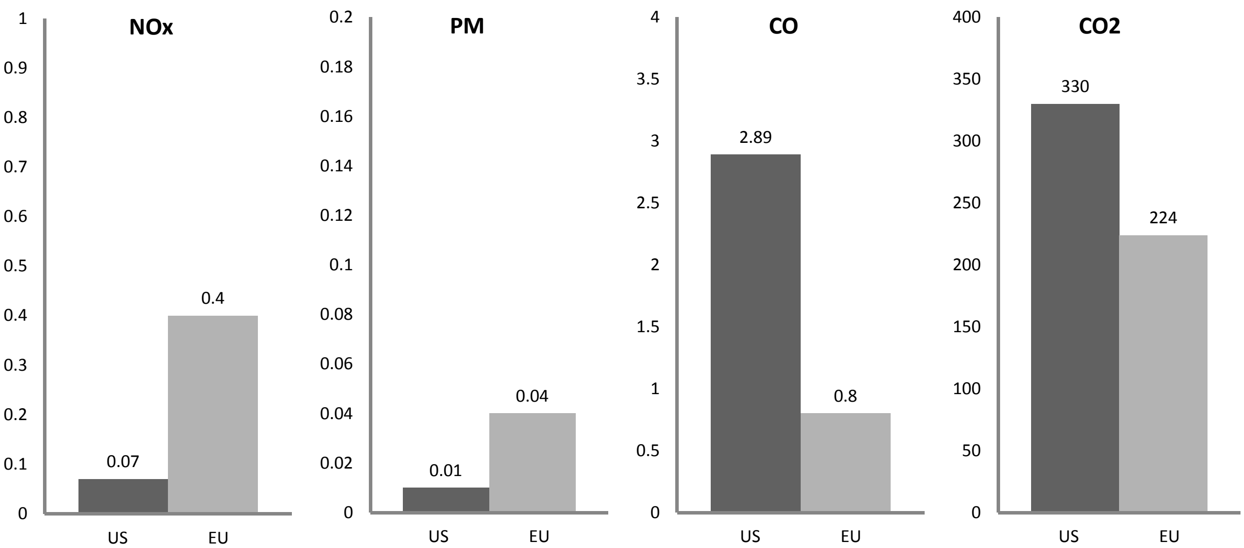
In this section we put forward the novel hypothesis that the different fate of diesels in Europe and the U.S. was instead due to the different goals pursued by the environmental policies in the U.S. and in Europe (Figure 5).[12] While Americans were concerned mostly with reduction in emissions leading to acid rain, Europeans aimed at reducing green house emissions.

[11] In Appendix E we use the estimated model to show the effect after the TDI's introduction was also small.

[12] European authorities set NO_x and particulate matter (PM) standards for each vehicle while U.S. authorities set a fleet-wide limit. As for CO and CO_2 emissions, these depend on fleet average fuel consumption standards and are reported in Figure 5 as realized fleet-wide levels. See Section IV of the 2001 report: "Demand for Diesels: The European Experience. Harnessing Diesel Innovation for Passenger Vehicle Fuel Efficiency and Emissions Objectives" available at `www.dieselforum.org`.

In the United States, the approval of the 1990 Clean Air Act Amendments (CAAA) directed the U.S. Environmental Protection Agency (EPA) to, among many other things, reduce acid rain produced by nitrogen oxide (NO_x) and sulfur dioxide (SO_2). The EPA therefore chose a policy largely aimed at power generating plants which set emission reduction goals (Title IV-A) and established a cap-and-trade system (Title V), but it also translated into an ever more stringent NO_x emission standards for light-duty vehicles (Title II-A).

Figure 5: Europe and U.S. Emissions Standards



Source: www.dieselforum.org. All statistics are for the year 2000 and are in grams per mile. "NOx" refers to nitrogen oxide limits; "PM" to particulate matter; "CO" carbon monoxide; and "CO2" carbon dioxide.

European regulators took a different approach and chose a less stringent emission standard on NO_x and PM (Figure 5).[13] While in 1994 U.S. Tier 1 standard allowed NO_x emissions of 1 gram per mile (g/mi), the Euro I standard was 1.55g/mi. By year 2000, the U.S. policy allowed only 0.07g/mi while the Euro III standard set the NO_x emission level at a far less demanding 0.4g/mi level. Similar results hold for PM. The fast diffusion of diesel vehicles in the 1990s likely also enabled European authorities to choose more stringent CO_2 emission standards than the United States; the goals of local automobile manufacturers and European environmental regulators were thus perfectly aligned. Were these differences in environmental goals enough to explain the different evolution of diesels in the U.S. and Europe? Absent any data on sales of automobiles by type of

[13] The negative health effects of PM are well documented. Capturing PM is however easier and far less expensive than capturing NO_x and we will not address it in our counterfactual analysis. See The World Bank's report: *Reducing Black Carbon Emissions from Diesel Vehicles: Impacts, Control Strategies, and Cost-Benefit Analysis* available at https://openknowledge.worldbank.org/bitstream/handle/10986/17785/864850WP00PUBL0l0report002April2014.pdf. In page 27 it indicates that the cost of complying with the most stringent PM emissions for a 4-cylinder 1.5 L diesel engine was $1,400 in 2014.

engine in the American market, we argue that this is the case based on anecdotal evidence for the U.S. and our counterfactual analysis for Europe.

The differences between the U.S. and European standards are significant for automobiles since reducing NO_x emissions is much harder for diesel engines as the three-way catalytic converters used to reduce emissions in gasoline engines cannot cope with the high concentrations of NO_x generated by diesel engines (*e.g.*, Canis 2012). Thus, rather than investing to redesign their diesel engines to meet these stringent emission standards, VOLKSWAGEN and MERCEDES chose to stop selling their diesel models in the U.S. market in 1993 and 1994, respectively, precisely at the time of the implementation of the U.S. emission standards mandated by the CAAA.[14] Only in 2010 did the EPA finally address the issue of NO_x emissions from diesel vehicles by requiring the installation of an urea-based selective catalytic reduction that injects an aqueous solution into the vehicles' exhaust stream to "scrub" NO_x emissions. Since then, auto makers have introduced more diesel models into U.S. market, including those states that adhere to the even more demanding California emission standards. All these circumstances suggest that the imposition of these emission standards amounted to a *de facto* ban of diesel vehicles in the U.S. market. Could then a similar European emission policy have eliminated any chance of success for diesels in Europe?

4 An Equilibrium Oligopoly Model of the Automobile Industry

In this section we present a structural equilibrium model of demand and supply which we use to discipline our analysis. We first present a standard *BLP* model of discrete choice demand with heterogenous customers. Then we describe an oligopoly model of supply in which multi-product firms comprising the several brands detailed in Table A.1 choose prices conditional on product characteristics (*e.g.*, car size).

4.1 Demand

Demand can be summarized as follows: consumer i derives an indirect utility from buying vehicle j at time t that depends on price and characteristics of the car:

$$\begin{aligned} &u_{ijt} = x_{jt}\beta_i^* - \alpha_i^* p_{jt} + \xi_{jt} + \epsilon_{ijt}\,, \\ &\text{where}\;\; i = 1,\dots,I_t; \quad j = 1,\dots,J_t; \quad t = \{1992,...,2000\}\,. \end{aligned} \tag{1}$$

[14] According to Stewart (2010), the NO_x emissions level of the least polluting diesel model available in Canada, the VOLKSWAGEN *Jetta* (known as *Bora* in Europe), was 0.915 and 0.927g/mi for the 1991 and 1997 year models, respectively. This indicates that the NO_x emissions standards imposed by the EPA were indeed binding constraints for diesel vehicles since even the cleanest diesel models barely met the 1994 U.S. emission standards and would have generated NO_x emissions thirteen times greater than the 2000 limit.

This Lancasterian approach makes the payoff of a consumer depend on the set of characteristics of the vehicle purchased, which includes a vector of K observable vehicle characteristics x_{jt} as well as others that remain unobservable for the econometrician, ξ_{jt}, plus the effect of unobserved tastes of consumer i for vehicle j, ϵ_{ijt}, which is assumed i.i.d. multivariate type I extreme value distributed. We allow for individual heterogeneity in response to vehicle prices and characteristics by modeling the distribution of consumer preferences over characteristics and prices as multivariate normal with a mean that shifts with consumer attributes:[15]

$$\begin{pmatrix} \alpha_i^* \\ \beta_i^* \end{pmatrix} = \begin{pmatrix} \alpha \\ \beta_t \end{pmatrix} + \Pi_t D_{it} + \Sigma_t \rho_{it} \,, \quad \rho_{it} \sim F \,. \tag{2}$$

Consumer i in period t is characterized by a d vector of observed demographic attributes, D_{it}, as well as a vector of random tastes, ρ_{it} distributed i.i.d. with cumulative distribution function F which is commonly assumed to be standard normal. Π_t is a $(n+1) \times d$ matrix of coefficients that measures the effect of income on the consumer valuation of automobile characteristics, *e.g.*, average valuation and price responsiveness. Similarly, Σ_t measures the covariance in unobserved preferences across characteristics. We decompose the deterministic portion of the consumer's indirect utility into a common part shared across consumers, δ_{jt}, and an idiosyncratic component, μ_{ijt}. The mean utilities of choosing product j and the idiosyncratic deviations around them are given by:

$$\delta_{jt} = x_{jt}\beta + \alpha p_{jt} + \xi_{jt} \,, \tag{3a}$$

$$\mu_{ijt} = \begin{pmatrix} x_{jt} & p_{jt} \end{pmatrix} \times \left(\Pi_t D_{it} + \Sigma_t \rho_{it} \right) \,. \tag{3b}$$

Consumers choose to purchase either one of the J_t vehicles available or $j = 0$, the outside option of not buying a new car with zero mean utility, $\mu_{i0t} = 0$. We therefore define the set of individual-specific characteristics leading to the optimal choice of car j as:

$$A_{jt} \left(x_{\cdot t}, p_{\cdot t}, \xi_{\cdot t}; \theta \right) = \left\{ \left(D_{it}, \rho_{it}, \epsilon_{ijt} \right) | u_{ijt} \geq u_{ikt} \quad \forall k = 0, 1, \ldots, J_t \right\} \,, \tag{4}$$

with θ summarizing all model parameters. The extreme value distribution of random shocks allows us to integrate over the distribution of ϵ_{it} to obtain the probability of observing A_{jt} analytically.

The probability that consumer i purchases automobile model j in period t is:

$$s_{ijt} = \frac{\exp\left(\delta_{jt} + \mu_{ijt} \right)}{1 + \sum\limits_{k \in J_t} \exp(\delta_{kt} + \mu_{it})} \,. \tag{5}$$

[15] Random coefficients generates correlations in utilities for the various automobile alternatives that relax the restrictive substitution patterns generated by the Independence of Irrelevant Alternatives property of the logit model.

Integrating over the distributions of observable and unobservable consumer attributes D_{it} and ρ_{it}, denoted by $P_D(D_t)$ and $P_\rho(\rho_t)$, respectively, leads to the model prediction of the market share for product j at time t:

$$s_{jt}(x_t, p_t, \xi_t; \theta) = \int_{\rho_t} \int_{D_t} s_{ijt} dP_{D_t}(D_t) dP_{\rho_t}(\rho_t)\,, \tag{6}$$

with s_{0t} denoting the market share of the outside option.

4.2 Supply

Equilibrium prices are found as the solution to a non-cooperative Bertrand-Nash game among the competing auto makers. Specifically, equilibrium prices (p_j^τ) can be written a nonlinear function of the product characteristics (x), market shares $s_j(x, p, \xi; \theta)$, retail prices (p), and markups:

$$p_j^\tau = mc_j + \underbrace{\Delta^{-1}(p, x, \xi; \theta) s_j(p, x, \xi; \theta)}_{b_j(p, x, \xi; \theta)}\,, \tag{7}$$

where $p_j = p_j^\tau \times (1 + \tau_j)$ and τ_j is the import duty applicable to model j, if any. The vector of equilibrium markups $b_j(\cdot)$ depends on market shares $s_j(\cdot)$ and the matrix $\Delta(\cdot)$ with elements:

$$\Delta_{rj}(x, p, \xi; \theta) = \begin{cases} \dfrac{\partial s_r(x, p, \xi_t; \theta)}{\partial p_j} \times \dfrac{\partial p_j}{\partial p_j^\tau}\,, & \text{if products } \{r, j\} \in \mathcal{F}_f\,, \\ \\ 0 & \text{otherwise}\,. \end{cases} \tag{8}$$

In estimating costs we make a common assumption that firms have Cobb-Douglas cost functions of the following (log-linear) form:

$$\log c_j = \sum_k \gamma^k \log(X_j^k) + \underbrace{\gamma^\xi \xi_j + \eta_j}_{\omega_j}\ . \tag{9}$$

Marginal costs are therefore a function of both observed and unobserved product characteristics, via X and ξ, and an unknown (to the econometrician) cost component η. Explicitly modeling ξ in the cost function does two things. First, it illustrates the potential endogeneity and subsequent estimation bias in the supply-side estimation since movements in ξ will be captured in ω in any standard *BLP* model. Second, it provides the structure to account for changes in unobserved product attributes ξ on marginal cost, *i.e.*, $\partial c/\partial \xi$. This is particularly relevant in our case as many features likely driving the cost of diesel vehicles such as torque, reliability, and durability remain unobservable to us.

5 Estimation

The common estimation approach employed by researchers using the *BLP* framework is to assume exogeneity of product characteristics so that $E[\xi|X] = 0$ and $E[\omega|X] = 0$. One can then estimate the demand and supply parameters $(\Sigma, \Pi, \beta, \gamma)$ using observable product characteristics as basis functions to construct identifying moment conditions.

In this section we describe an alternative estimation approach which follows Petrin and Seo (2016). The advantage of this approach is that it allows us to estimate the key demand and supply parameters with limited restrictions on the relationship between the observable (X) and unobservable (ξ) product characteristics. To do so we extend the model described in Section 4 as follows: each period multi-product automobile manufacturers choose the characteristics of their products (both the K observed and the unobserved ξ), understanding that these characteristics determine the retail prices via equation (7). In a Bayes-Nash equilibrium the chosen product characteristics (and the ensuing retail prices) maximize profits conditional on each firm's belief about the actions of its rivals. Mathematically, each multi-product firm f chooses product characteristics x_j^k in period t to solve:

$$\max_{x_{jt}^k} E\left[\sum_{r \in \mathcal{F}_{ft}} (p_{rt} - c_{rt}) \times s_{rt}(x, p, \xi_t; \theta) \,\Big|\, \Psi_t^f\right], \tag{10}$$

where $\mathcal{F}_{ft}$ is the set of vehicles of all brands sold by firm f and Ψ_t^f is its period t information set which may include any information available to the firm in period t (*e.g.*, observable and unobservable product characteristics).[16] To simplify notation going forward, we drop t subscripts and will note when timing considerations are important. The subsequent optimal pricing strategy will be a function of product positioning of all competing firms. Thus, in choosing product attributes, profit maximization yields the following first order condition:

$$E\left[\frac{\partial(p_j - c_j)}{\partial x_j^k} \times s_j + \sum_{r \in \mathcal{F}_f} (p_r - c_r) \times \frac{\partial s_r}{\partial x_j^k} \,\Big|\, \Psi_t^f\right] = 0\,, \tag{11}$$

[16] While allowing a firm to choose observable product characteristics may be intuitive, it is worthwhile to provide some intuition as to what it means for a firm to choose an unobservable product characteristic. For example, in equation (10) we allow a company such as AUDI to both increase the fuel efficiency (observable to us) and reliability (not observable to us) of a car in its portfolio. The latter choice is captured in the model via an increase in ξ, though of course AUDI could choose other factors which ultimately increase demand through ξ. Ignoring this relationship leads to a violation of product characteristic exogeneity and biases estimation results. Of course, a cleverly chosen set of control variables would also remove any exogeneity concerns (*e.g.*, Nevo 2000), but this is often difficult in practice. An advantage of our approach is that we can be agnostic about the controls in the estimation and test for exogeneity afterwards.

where:

$$\frac{\partial s_r}{\partial x_j^k} = \begin{cases} \int_{\rho^k} \int_D (\beta^k + \sigma^k \rho^k + \pi^k D) \times s_{ij}(1 - s_{ir}) dP_D(D) dP_\rho(\rho) + \sum_{m \in \mathcal{F}_f} \frac{\partial s_r}{\partial p_m} \frac{\partial p_m}{\partial x_j^k}, & r = j, \\ -\int_{\rho^k} \int_D (\beta^k + \sigma^k \rho^k + \pi^k D) \times s_{ij} s_{ir} dP_D(D) dP_\rho(\rho) + \sum_{m \in \mathcal{F}_f} \frac{\partial s_r}{\partial p_m} \frac{\partial p_m}{\partial x_j^k}, & \text{otherwise}. \end{cases} \tag{12}$$

In the *BLP* framework product attributes are taken as given even though they determine pricing strategies and the ability to charge a higher or lower markups depending on the product positioning of all firms. Profit maximization conditions (11)-(12) describe an alternative framework where firms first choose product characteristics while taking into account the expected impact of these choices on profits through retail prices facing consumers and the induced cross-price effects on the demand of other products offered by the firm. Product attributes and prices are chosen sequentially so firms do not respond by changing attributes to respond to prices as in a model where prices and attributes were chosen simultaneously. Thus, product characteristics, observed or unobserved, condition the optimal pricing strategies that are set in equilibrium.

5.1 Estimation Details

Our estimation must account for several important changes taking place during the 1990s such as increasing personal income, reduction of import duties, and multiple mergers of automobile manufacturers as well as differences in the information available to firms when they choose product characteristics. When estimating the model we simulate individuals from yearly census data to account for growth in income and the expansion of the Spanish economy (time-varying outside option). Similarly, the marginal cost equation (Equation 7) controls for relevant import taxes faced by manufacturers depending on their national origin and varies over the period considered. To account for changes in firms' product portfolios, we update matrix Δ_{rj} every year to match the ever changing ownership structure of this industry during the 1990s and correctly define the multi-product first-order profit maximization conditions of the equilibrium model to be estimated.[17]

The final task is to map the firm information sets, Ψ_t^f, into pay-off relevant beliefs about rivals actions. Unfortunately, there is no clear way to construct the mapping *ex-ante* as it is unclear the degree to which firms in this industry are knowledgeable of the likely innovation decisions of their rivals or of the tastes of consumers today conditional on their previous purchase decisions. We instead take a simpler approach and impose these beliefs directly using two likely candidates. Under "Model 1" we make a similar assumption to Hansen and Singleton (1982) and allow period t

[17] See Appendix A for details on acquisitions and mergers in the European automobile industry during the 1990s.

firms to know all period $t-1$ product characteristics of their rivals. We also assume that firms can observe (or at least infer) the unobserved characteristics (ξ) driving consumer purchase decisions. The structural errors (ν) then are due to either these information (or belief) asymmetries or measurement error. We treat this estimation as a likely conservative approach since the underlying assumed information/ belief structure may reflect lags between product design and pricing once vehicles are developed and sold. In "Model 2" we allow firms to know both the period t observable and unobservable characteristics of their rivals. The interpretation behind the structural errors (ν) then is that of measurement error.[18] We view this estimation as a bound to identify the robustness of our estimates to alternative belief structures where firms have near perfect foresight, *i.e.*, the case where details of product developments are common knowledge among automobile manufacturers.

5.1.1 *The GMM Estimator* As in the standard *BLP* estimation approach we estimate the structural parameters of the model by GMM as in Hansen and Singleton (1982). Define the parameter vector $\theta = [\beta, \Sigma, \Pi, \gamma]$. First, we solve for the mean utilities $\delta(\theta)$ using the standard contraction mapping outlined in Appendix I of *BLP*. Next we solve for the implied markups b_{jt} and use price data to construct marginal costs, assuming a pure strategy Bertrand-Nash equilibrium. In principle, these first-order conditions of equation (11) are necessary for any Bayes-Nash equilibrium with multiple interacting players, although meeting these conditions does not rule out the possibility of multiple equilibria nor does it imply a restriction regarding the equilibrium selection mechanism should multiple equilibria exist. We follow Bajari, Benkard and Levin (2007) and use the data – the observed product, price, and consumption choices – as the equilibrium selection mechanism which is sufficient provided the data is generated by a single equilibrium.

We construct the structural error $\nu_j^k(\theta)$ as follows:

$$\nu_j^k(\theta) = \frac{\partial[p_j^\tau - c_j(\theta)]}{\partial x_j^k} \times s_j(\theta) + \sum_{r \in \mathcal{F}_f} [p_r^\tau - c_r(\theta)] \times \frac{\partial s_r(\theta)}{\partial x_j^k} \,. \tag{13}$$

The evaluation of the response of demand for all products of each firm to each change in product characteristics makes this task particularly computationally-intensive as it requires solving repeatedly for the equilibrium price responses due to changes in product characteristics in addition to evaluating numerically the multiple integrals of equation (12).[19]

Profit-maximization requires that in each period t the expectation of the structural error ν conditional on the firm beliefs, Ψ_t^f, is zero for all products and characteristics, *i.e.*, $E[\nu_{j,t}^k(\theta)|\Psi_t^f] =$

[18] For example, using manufacturer's suggested retail price (MSRP) rather than transacted price – a common feature of automobile data (and present in *BLP*) – likely introduces error into the pricing game which could materialize in deviations in the first-order conditions.

[19] We provide specific details of the solution algorithm in Appendix B.

0). Moreover, any function of variables in the information set are valid instruments so the set of potential instruments is large. Following Newey (1990) we assume that:

$$\Omega(\hat{\theta}) = E[\nu(\hat{\theta})'\nu(\hat{\theta})]\,, \tag{14}$$

is a constant square matrix which defines the covariance structure of optimization errors where $\nu(\hat{\theta}) = [\nu_{\cdot,t}^{k=1}(\hat{\theta}), ..., \nu_{\cdot,t}^{k=K+1}(\hat{\theta})]$ is a matrix of structural errors and $K+1$ is the number of endogenous characteristics chosen by firms.[20] Chamberlain (1987) shows that we can use the model to generate instruments defined below:

$$H_{jt}(\hat{\theta}) = E\left[\frac{\partial \nu_{jt}(\hat{\theta})}{\partial \hat{\theta}}\Big|\Psi_t^f\right]'\Omega^{-1}\,. \tag{15}$$

where H_{jt} is N-by-$(K+1)$ matrix with N corresponding to the number of elements in $\hat{\theta}$. The logic behind these instruments is straightforward: they place relatively more weight on observations that are responsive to deviations of the parameter vector in a neighborhood of the estimated value. Since the value of the structural error ν is dependent upon the assumed information structure, so are the instruments.

We estimate θ using a commonly employed two-step GMM estimation. Specifically, in each step we solve for the value of the GMM objective function conditional on θ by interacting the structural errors (13) with the identifying moment conditions (15) as follows:

$$\theta^\star = \underset{\theta}{\operatorname{argmin}}\, G(\theta)A^{-1}G(\theta)'\,, \tag{16}$$

where $G(\theta) \equiv E[\tilde{\nu}(\theta)' \times \tilde{H}(\hat{\theta})]$, $\tilde{\nu}(\theta) = [\nu^{k=1}(\theta); ...; \nu^{k=K+1}(\theta)]$ is a stacked vector of structural errors, and A^{-1} is a positive-semidefinite weighting matrix that exists because there are $(K+1)$ instruments for each element of θ, *i.e.*,

$$\tilde{H}(\hat{\theta}) = \begin{bmatrix} H^1(\hat{\theta}) & \dots & 0 \\ \vdots & H^k(\hat{\theta}) & \vdots \\ 0 & \dots & H^{K+1}(\hat{\theta}) \end{bmatrix}. \tag{17}$$

The estimator exploits the fact that at the true value of parameters $\theta^\star$, the instruments $\tilde{H}$ are orthogonal to the errors $\tilde{\nu}(\theta^\star)$, *e.g.*, $E\left[\tilde{H}' \times \tilde{\nu}(\theta^\star)\right] = 0$. In the initial step we solve for $\tilde{H}$ and A^{-1} using the parameter estimates when we assume product characteristic exogeneity (*i.e.*, a standard *BLP* estimation). In constructing the weighting matrix, we allow for the structural errors

[20] See Newey (1993) for the case of heteroscedasticity.

ν within a car model to be correlated across characteristics and time. We then update $\hat{\theta}$ by solving (16) and using this value to update the instrument and weight matrices. We found additional updates changed our estimates little.[21] To ensure robustness of our GMM results we employed a state-of-the-art estimation algorithm (KNITRO) shown to be effective with this class of models; considered a large variety of initial conditions; and used the strict inner-loop convergence criterion for calculating the mean utility δ suggested by Dubé, Fox and Su (2012).

As a final step we identify systematic trends in estimated unobserved demand, $\hat{\xi}$, and cost, $\hat{\eta}$, by projecting these vectors onto a set of dummy variables (*e.g.*, diesel, segment, firm) and time trends. We view these results as descriptive as many factors could be driving why consumers prefer European cars to foreign cars or why ALFA ROMEO is, *ceteris paribus*, more expensive to produce than RENAULT.

5.1.2 Specification Consumer demand (both mean and idiosyncratic) includes measures of automobile performance: horsepower divided by weight (HPW) and exterior dimensions (SIZE). We also include the fuel cost of driving, (KPE), as a "random coefficient" but we assume the distributions for ρ_{KPE} is distributed i.i.d. exponential, therefore ρ_{KPE} plays a dual role, controlling not only the mean valuation but also the substitution pattern within fuel (in)efficient vehicles. The advantage of this approach is that *ex-ante* all agents value fuel-efficient cars (*i.e.*, will value paying less to get from point A to point B) though we allow agents to be heterogenous in how much they value fuel-efficient cars (*e.g.*, some agents may value producing less emissions of some kind, *e.g.*, CO_2 or NO_x). We also include random coefficients for DIESEL to generate different substitution within the diesels and a CONSTANT to capture changes in substitution patterns due to the increasing product set. We limit the demographic interactions (Π) to be just an interaction between price and income as described in Section 4.1.

On the supply side, we include the logged values of the observed product characteristics (HPW, SIZE, and KPE) with some modifications. We replace KPE, which includes the effect of fluctuations in the price of oil, with a measure solely based on fuel-efficiency, C90. Consequently, AUDI's choice of fuel-efficiency for a gasoline model A4 impacts its cost directly as measured by C90, but demand for A4's will also be influenced by changes in the price of gasoline due to economic factors outside of AUDI's control. Hence, we include KPE in the demand rather than in the supply equation. Similarly, we allow for increasing steel prices to impact the cost of producing larger, heavier cars by multiplying car weight and size by an index for the price of steel. This leads to shifts of HPW and SIZE in supply but not demand.

[21] In principle one could make the problem just-identified by stacking the $H^k(\hat{\theta})$ matrices. We found this approach led to unrealistic variation in marginal costs, particularly across brands.

As mentioned above, the GMM estimation generates estimates of unobserved demand, $\hat{\xi}$, and supply, $\hat{\omega}$, which we project onto a set of dummies to identify systemic patterns in demand and cost. As our sample period covers the diffusion of diesel vehicles, we include a DIESEL dummy as well as a linear time interaction with DIESEL in order to capture the evolution of preferences in favor of the new technology. We also include segment dummies allow for differences in demand between, for example, minivans and luxury cars. Finally, we include a NON-EU dummy to account for differences in valuation of largely Asian imports in the European market and a dummy variable for the national brand, SEAT, to evaluate possible home bias effects.

5.1.3 Parameter Identification This model represents a complex, nonlinear mapping from parameters to data, though the intuition behind our estimation approach is straightforward. In the model consumers maximize utility by evaluating a car based not only price but also product characteristics, some of which are unobserved to the researcher but known to consumers and firms. In Section 2.3 we documented that there is variation in product characteristics over the decade. Our estimation then uses the firms' choices in product characteristic space to reveal the underlying demand and cost parameters via the correlation between the unobserved shocks (in both demand and cost) and observable product characteristics. For example, if car size is positively correlated with reliability and the latter increases consumer utility, VOLKSWAGEN's choice to produce large, reliable cars provides information regarding the utility associated with car size in our estimation whereas the two are assumed exogenous in the standard *BLP* approach leading to a biased estimator.

While there is no clear one-to-one mapping between a parameter and a specific moment in the data, the intuition into how data variation identifies different components of θ is as follows. Variation in the product set, product characteristics (*e.g.*, SIZE), prices, and quantities identifies the random coefficients, Σ. We also include a random coefficient for diesel which is identified by variation in the other moment conditions by fuel type. A similar argument holds for the constant random coefficient which is identified by variation across moment conditions as the number of products increase.[22] Finally, the Bertrand-Nash pricing equilibrium plus variation in price elasticities conditional on product characteristics identifies marginal costs, γ.

The intuition behind the identification of α (*i.e.*, Π) is embedded in the structural error $\nu(\theta)$ – Equation (13) – where the key tension is between the objects $(p-c)$ and $\frac{\partial[p_j^{\tau}-c_j(\theta)]}{\partial x_j^k} \times s_j(\theta)$.

[22] Note that a firm's choice to offer a model with a diesel engine is a discrete choice while the structural errors implied by the first-order conditions, equation (13), are based on continuous characteristics. An alternative approach would be to redefine ν to include moment inequalities for diesel engines as in Pakes, Porter, Ho and Ishii (2015). Unfortunately, identifying the cost of introducing a diesel engine is difficult since automakers usually introduce a diesel engine option soon after launching a new gasoline car model (rather than introducing a diesel engine option in an existing car model) so constructing these moment inequalities may not be informative. Since our model is over-identified we chose a simpler approach and ignored this endogenous choice (*i.e.*, do not include a moment inequality on the optimality of offering car j as diesel).

As $\alpha \uparrow 0$ consumers become less price-sensitive and the markups implied by our Bertrand-Nash pricing equilibrium increase, driving down estimated marginal costs and increasing $(p - c)$. This effect is also true in *BLP*. The innovation here then is the second term, $\frac{\partial [p_j^\tau - c_j(\theta)]}{\partial x_j^k} \times s_j(\theta)$, which becomes large as consumer demand becomes more inelastic. As this term reflects the sensitivity of price to changes in product characteristics, allowing for product characteristic endogeneity enables the researcher to use changes in product characteristics to also infer market-power via α. As we will see below, adding this additional level of identification leads to demand estimates which are much more elastic.

5.2 Estimation Results

Estimation results are presented in Table 2. Overall, the estimates are reasonable, statistically significant, and congruent with the descriptive evidence of the industry of Section 2. We also observe little difference between Models 1 and 2 suggesting the information sets we considered played only a minor role. For brevity, we will largely refer to the estimation results from Model 1.

Starting with costs, diesels are more expensive to manufacture than gasoline models. Marginal cost of production are also higher for larger and more powerful cars. Marginal cost is decreasing in fuel efficiency (increasing in C90) in both specifications of our full model, though the effect is small and not statistically different than zero when we condition firm decisions on the previous year's product characteristics. It also appears that there are no important efficiency gains occurring during the decade but rather a small long term increase in cost of production perhaps driven by factors associated to the long term increase in sales of larger and more powerful vehicles during the 1990s. Finally, costs are also increasing in the unobserved quality attribute, ξ. This may include better performance measured as reliability (or torque for diesel vehicles) as well as cost associated to setting up dealership networks for Asian newcomers.

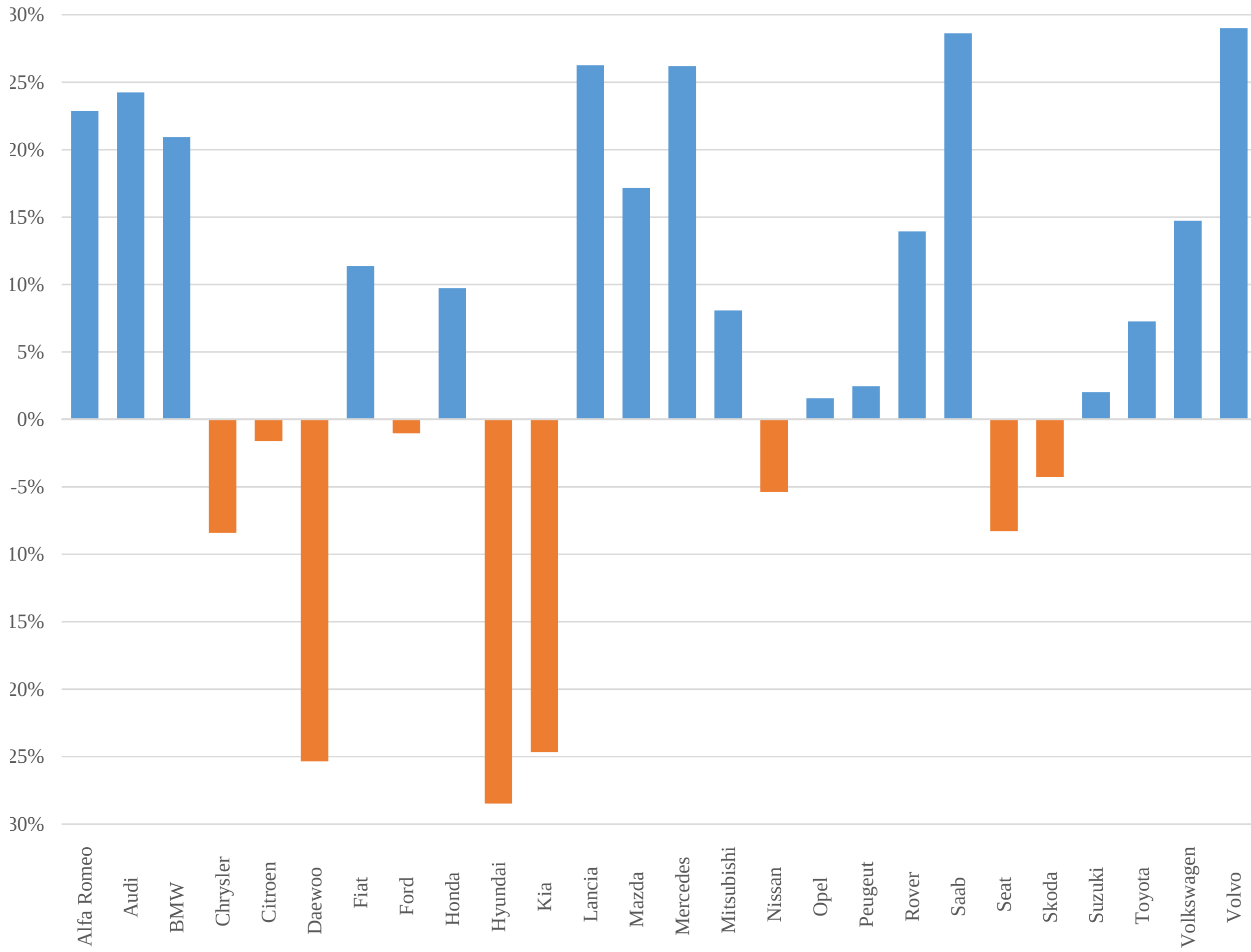
In Figure 6 we report differences in marginal costs across brands relative to the Spanish market leader, RENAULT. Results are very reasonable, capturing the common perception of the automobile market in Spain. German upscale brands AUDI, BMW, and MERCEDES, are among the most expensive to produce. Chrysler (U.S. based) and Asian imports are quite competitive, with Korean imports DAEWOO, HYUNDAI, and KIA, averaging a 26% relative cost advantage. European manufacturers with lower unit costs of production than RENAULT, include the Czech brand SKODA and the old Spanish brand SEAT, both of them acquired by VOLKSWAGEN to sell streamlined versions of their vehicles targeting lower income customers. Another interesting case of relatively low cost of production is FORD, which produces most of its smaller European models in a large plant located in Spain. These results reassure us that our specification is reasonable and that our estimates will be helpful in evaluating meaningful counterfactuals.

Table 2: Demand and Supply Estimates for Different Specifications

	Model 1		Model 2		"BLP"	
	Coefficient	Rob. SE	Coefficient	Rob. SE	Coefficient	Rob. SE
Standard Dev. (σ)						
HPW	1.6258	(0.2060)***	0.6576	(0.3736)*	3.9037	(0.3717)***
KPE	1.8003	(0.0908)***	1.9627	(0.0665)***	2.1083	(0.2665)***
DIESEL	6.8429	(1.2848)***	7.1065	(1.4239)***	7.0359	(0.3987)***
CONSTANT	3.8922	(0.8962)***	5.6884	(0.7858)***	2.1011	(0.3579)***
Interactions (Π)						
PRICE/INCOME	−4.3618	(0.3875)***	−4.4068	(0.3404)***	−2.1563	(0.1764)***
Mean Utility (β)						
HPW	−0.0770	(0.3687)	0.5972	(0.2105)***	3.9996	(1.3082)***
SIZE	5.0385	(0.3084)***	5.9951	(0.3246)***	5.7068	(1.0388)***
DIESEL	−9.6992	(0.2064)***	−9.5499	(0.2092)***	−10.6753	(0.8381)***
DIESEL × TREND	0.5579	(0.0416)***	0.6271	(0.0420)***	0.5016	(0.0386)***
NON-EU	−1.4706	(0.1187)***	−1.4944	(0.1204)***	−1.1276	(0.1713)***
SEAT	0.0491	(0.1756)	0.0542	(0.1758)	0.8839	(0.2791)***
COMPACT	1.2363	(0.1364)***	1.1549	(0.1372)***	−0.4341	(0.3178)
SEDAN	2.4353	(0.1314)***	2.3257	(0.1329)***	−0.2111	(0.3842)
LUXURY	4.7115	(0.1914)***	4.6207	(0.1933)***	−0.2913	(0.4702)
MINIVAN	2.1268	(0.1629)***	2.0407	(0.1632)***	−0.3776	(0.4149)
CONSTANT	−13.1307	(0.1663)***	−16.7843	(0.1684)***	−15.5799	(1.2450)***
TREND	0.0766	(0.0293)***	0.0897	(0.0298)***	0.0087	(0.0214)
Cost (γ)						
ln(HPW × STEEL PRICE)	0.2138	(0.0308)***	0.2502	(0.0317)***	0.8121	(0.0657)***
ln(SIZE × STEEL PRICE)	1.0090	(0.0956)***	1.1696	(0.0900)***	2.5370	(0.1678)***
ln(C90)	0.0211	(0.0130)	0.0308	(0.0121)**	0.2727	(0.0711)***
UNOBSERVED DEMAND (ξ)	0.0711	(0.0097)***	0.0585	(0.0076)***		
CONSTANT	0.7123	(0.0158)***	0.8375	(0.0148)***	−0.0857	(0.1528)
TREND	0.0159	(0.0018)***	0.0129	(0.0017)***	−0.0011	(0.0038)
DIESEL	0.8333	(0.0132)***	0.7073	(0.0126)***	0.3662	(0.0354)***
Elasticity Statistics:						
- Average	5.7		5.9		3.1	
- Maximum	18.4		18.4		10.6	
- Minimum	2.9		3.1		1.4	
Margin Statistics (%)						
- Average	20.3		19.7		37.7	
- Maximum	38.1		36.1		74.7	
- Minimum	4.9		5.0		10.0	
Estimation Statistics						
Number of observations	1,740		1,740		1,740	
Simulated agents per year	5,000		5,000		5,000	
Information Set	$X_{t-1}, W_{t-1}, \xi_{t-1}$		X_t, W_t, ξ_t		N/A	
J-Statistic	52.9		42.6		151.9	

Robust standard errors in parentheses. Significant estimates with p-values less than 0.1, 0.05, and 0.01 are identified with *, **, and ***, respectively. Cost fixed effects for brand and segment not reported. [b] Estimates based on projecting the estimated values of the demand unobservable ξ on other demand characteristics, including segment fixed effects and a time trend. "Margin" defined as $100 \times \frac{p-c}{p}$ where price excludes import tariffs, if applicable. Equilibrium prices account for year-specific ownership structure as reported in Appendix A (Table A.1).

Figure 6: Production Costs Differences Across Brands
(Reference: Renault)

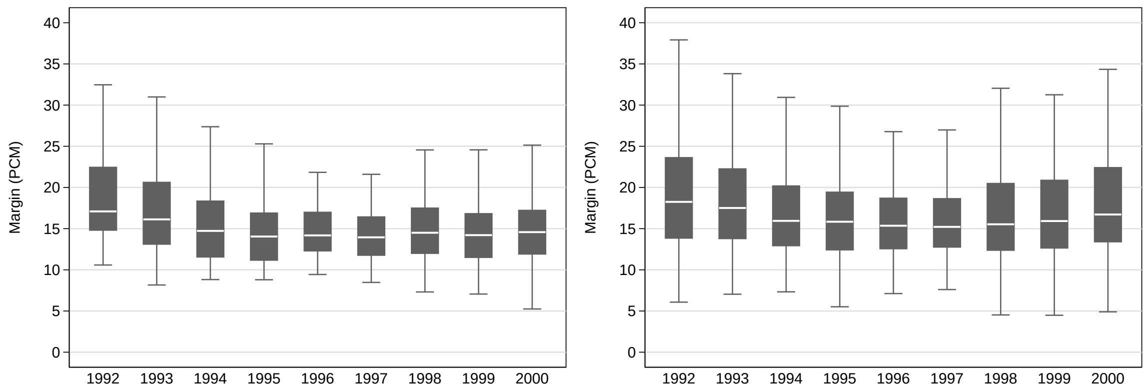


As for demand, Table 2 shows that it is downward slopping and always elastic. Both specifications of full model generate similar price elasticities and price-cost margins. Using the first specification as the benchmark, we estimate an average estimated price elasticity around 5.7 implying an average of 20% margin for the Spanish automobile industry during the 1990s. There is however substantial heterogeneity, with margins as low as 4.9% and as high as 38.1 percent. This wide range of margins are due to heterogeneous valuation of cars' characteristics at a moment in time, the evolution of preferences over time, and the changing product offering over the decade.[23] Figure 7 shows that average estimated margins, both of gasoline and diesel vehicles, remain quite stable, only decreasing very slightly during the middle 1990s for gasoline models. In the case of diesel vehicles margins are relatively large at the beginning of the decade but they fall as the decade proceeds due to increased imitation and competition in the segment. At the same time, consumer

[23] Although ignoring the distinction between diesel and gasoline models, Moral and Jaumandreu (2007) show that demand elasticities are smaller but also very heterogeneous across market segments and product life cycle.

preferences towards diesels are improving ($\beta_{Diesel \,\times\, Trend} > 0$) so the net effect is to stabilize diesel margins over the latter half of the decade. For both engine types, the dispersion of margins grows during the last three years of the sample as a growing economy increases dispersion of consumer incomes.

Figure 7: Evolution of Estimated Price-Cost Margins (Model 1)



(a) Diesel Vehicles (b) Gasoline Vehicles

Estimates of Table 2 show that after we control for price and fuel efficiency, drivers prefer larger cars (positive coefficient for SIZE) even after controlling for segment. The average consumer is indifferent about performance (insignificant coefficient for HPW in mean utility) but, not surprisingly there is a great deal of heterogeneity as captured through the significant random coefficient for HPW. The negative and significant sign of NON-EU is an empirical regularity in the international trade literature and is commonly referred to as the "home bias" effect.[24] Since our focus is on a specific industry rather than a set of bilateral trade flows across many sectors, we can provide a more detailed interpretation. At this time, Asian imports were first sold in the European market and were considered low quality, fuel-efficient alternatives to European vehicles but they lacked both brand recognition as well as a widespread network of dealerships for maintenance. Thus, the negative sign of NON-EU is not surprising.

The large and significant value for KPE as a random coefficient indicates that Spanish drivers are both concerned with fuel efficiency on average while their heterogenous tastes towards fuel efficiency leads to different substitution patterns between fuel-efficient and fuel inefficient vehicles. The results also indicate that some drivers strictly prefer diesel vehicles while on average diesels are relatively unpopular after controlling for their primary competitive advantage, fuel efficiency.

We have thus far appealed to intuitive arguments to justify why we expect that observed and unobserved product characteristics are likely to be correlated. Now that we have estimated the model and recovered the unobserved quality index ξ, we can corroborate our intuition. Table 3

[24] See Cosar, Grieco, Li and Tintelnot (2015) for estimates of cross-country home bias in the automobile industry.

Table 3: Are Product Characteristics Correlated?

	SIZE	HPW	$\hat{\xi}$
HPW	1.0000		
	-		
SIZE	0.3921	1.0000	
	(0.0187)	-	
$\hat{\xi}$	0.7171	0.3109	1.0000
	(0.0128)	(0.0199)	-

Notes: Estimated unobserved product characteristics ($\hat{\xi}$) based on previous year characteristics (*i.e.*, Model 1).Standard errors reported in parentheses.

presents the correlations between the observable product characteristics included in the *BLP* estimation and the estimated unobserved product characteristic $\hat{\xi}$ implied by our alternative estimation approach. The reported results provide clear evidence that the observed and unobserved product characteristics are indeed very much correlated – consistent with the results of Petrin and Seo (2016).

The natural question then is whether these correlations are quantitatively important. In Table 2 we juxtapose estimates from our full model with estimation results when we assume that product characteristics are exogenous (model "BLP"). In an attempt to keep the specifications as close as possible to each other, we maintained the same set of random coefficients and demographic interactions as well as the same simulated agents. We also included the post-GMM regressors from our full model into the GMM *BLP* estimation. Our only departure from Berry et al. (1995) pertains to the instruments which we found uninformative for our data. Instead we employed "differentiation IVs" introduced by Gandhi and Houde (2015). The idea is similar to the concentration instruments proposed in Berry et al. (1995) but instead of simple sums or averages (*e.g.*, sum of HPW for products not owned by the producer of product j in period t), we include summary statistics for the distribution of distances in product space (*e.g.*, average distance in HPW of products not owned by the producer of product j *and* far away from product j in HPW space).

The comparison reveals that assuming orthogonality produces significant estimation biases. The most striking feature between the estimation approaches is the difference in the price coefficient where we find a much smaller value when we impose product exogeneity, leading to lower estimated price elasticities and higher estimated markups. We also find larger random coefficients for HPW and KPE but a smaller random coefficient for the constant. The model's overall fit is also poor – a common result among *BLP* models – reflected in a J-statistic of 151.9 which is substantially greater than the 95% critical value. All of this leads us to reject the assumption of product characteristic exogeneity.

6 Emissions Policy as Industry Protection

In this section we present evidence that emissions standards did indeed drive the rise of diesels in Europe. Said differently, we show that had the EU imposed more rigorous NO_x emissions standards the diffusion of diesels would have been much smaller. The trade implication of such policies are significant – a near doubling the import share from 11.8 to 19 percent. By not adopting such damaging policies, whether inadvertently or not, European policymakers implicitly helped European manufacturers enhance their dominance in the domestic market. To our knowledge this is the first time a structural equilibrium model of oligopoly industry competition in differentiated products has been used to evaluate trade frictions, in particular the trade protective impact of environmental regulation.

We model a change in emissions policy as an in increase in marginal cost applicable only to diesel vehicles. We think of this "retrofitting" cost as the additional equipment required to make the diesel fleet compliant with the new standard. We assume that all diesel models require the same cost. The task then is to identify a "realistic" cost to retrofit an auto maker's diesel fleet to the new standard. For years, a technology to successfully capture NO_x emissions at the tailpipe simply did not exist. When it finally became available, in the late 2000s, it was still very expensive. By the EPA's own estimates in 2010, diesel engines could be retrofitted to comply with both EPA and California NO_x emission standards by means of a *Lean NO_x Catalyst* at an estimated cost of between \$6,500 to \$10,000 per vehicle. Lean NO_x catalysts use diesel fuel injected into the exhaust stream to create a catalytic reaction and reduce pollution. However, these catalysts still require specific exhaust temperatures for appropriate NO_x emission control performance, and on average they reduce emissions up to a maximum of 40%. German manufacturers BMW and MERCEDES were certified to be sold in all 50 states of the U.S. in 2009 only after equipping their new vehicles with a *Selective Catalytic Reduction System* that injects a reluctant (a urea-based solution) into the exhaust stream where it reacts with a catalyst to convert NO_x emissions to nitrogen gas and oxygen. This system is more effective, reducing NO_x emissions up to 75% but the EPA estimated that its cost ranged between \$10,000 and \$20,000 per vehicle in 2010.[25]

Computing the equilibrium of a counterfactual environmental policy reintroduces issues about multiple equilibria as firms could potentially adjust both product characteristics and prices in response to an alternate regulation. Rather than computing all potential equilibria and evaluating the consequences of each, we take a simpler approach and keep the product characteristics fixed

[25] On retrofitting costs see *Diesel Retrofit Devices.* EPA's National Clean Diesel Campaign, 2013. `http://www.epa.gov/cleandiesel/technologies/retrofits.htm` as well as our summary in Appendix C.

while allowing firms to re-optimize their prices.[26] While there is no guarantee of uniqueness in the pricing game either, we've found little evidence of multiple equilibria as solving the pricing game from different initial conditions leads to the same equilibrium.

We believe this simpler approach is indeed a good first-order approximation to the short-term (*i.e.*, the 1990s) impacts of alternative emissions and fuel taxation policies. Evidence suggests that product innovations in this industry are slow as redesigning a car's size, engine, drive-chain, *etc.* is costly and time-consuming – an issue consistent with our estimation. This is likely particularly true for changes in the characteristic which diesels hold a competitive advantage, fuel efficiency, since designing and redesigning engines are both extremely expensive and time consuming.[27] This would suggest that our results are best thought of as a realistic approximation for the short-term (though still denominated in years) effects of emissions policy, while the longer term (*i.e.*, 10-20 years) are unclear.

Our final task is to choose a benchmark set of estimation results which we can then use to assess the implications of different emissions policies. Given the above results we choose the model in which firms form expectations using the previous year's product set as our benchmark (*i.e.*, Model 1). Our rationale is that this information set demands far less knowledge and foresight from the firms. Since both specifications of the full model generate similar demand and cost estimates, our selection of this model, fortunately, has little quantitative or qualitative implication on our results.

6.1 Consumer Response to a More Rigorous NO_x Policy

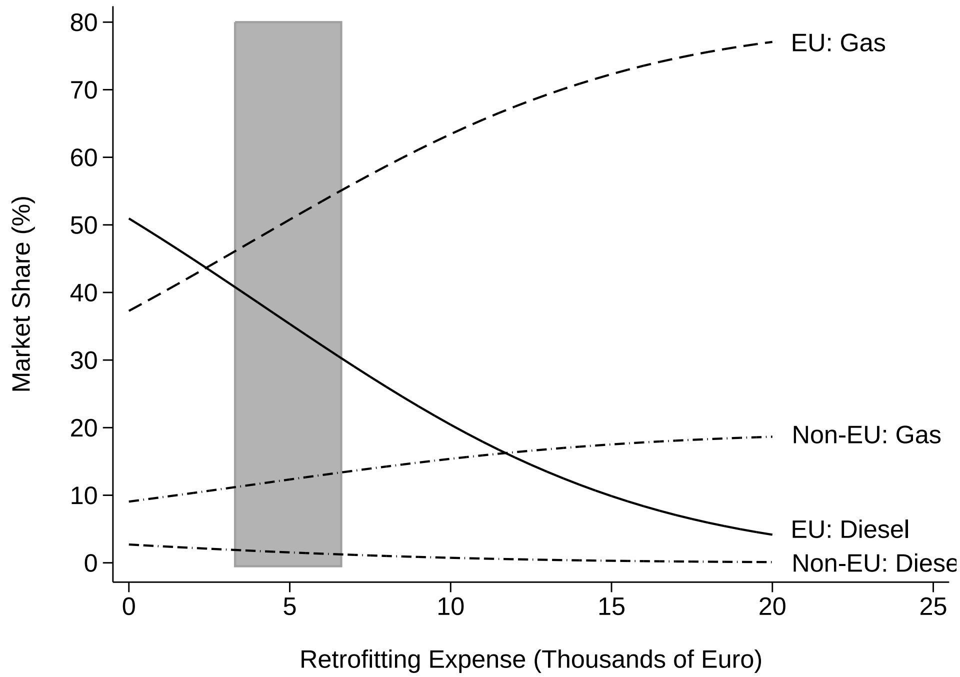
In Figure 8 we present the consumer response as we vary the additional cost of retrofitting expense (x-axis) required to make diesels compliant with a more rigorous NO_x emissions policy. The shaded area highlights the limits of the estimated EPA retrofitting costs corrected for the exchange rate and inflation.

Figure 8 shows that the increase in production costs required to comply with the more rigorous NO_x environmental regulation leads consumers to substitute away from diesel vehicles for even small retrofitting costs. At the lower bound for the EPA estimate, a retrofitting cost of

[26] Specifically, one could identify all potential equilibria using a homotopy algorithm as in Besanko, Doraszelski, Kryukov and Satterthwaite (2010). Although difficult, one could presumably evaluate the likely impact of a policy change by assessing commonalities between the equilibria (*e.g.*, change in diesel market share and profits). A complicating factor is that an alternative NO_x emissions policy would have likely impacted the evolution of consumer preferences for the diesel over the decade; a fact currently captured in the positive and significant estimate for the diesel trend variable $\beta_{Diesel \times Trend}$.

[27] Busser and Sadoi (2004, Footnote 2) document that since demand was small in their countries of origin, Asian manufacturers such as Toyota acquired engines from other European firms as a less costly way to satisfy European demand rather than investing in the development of diesel engines from scratch.

Figure 8: Market Shares, Quantity Sold, and Retrofitting Costs



€3,300, we already see a significantly negative impact on the popularity of diesel vehicles as diesel market share falls by 12 percent. At the upper bound, a retrofitting cost of €6,600, the market share of European diesel vehicles is nearly cut in half. For a retrofitting cost of €12,000 the market share of European diesels returns to the level observed at the beginning of the sample and below the share of gasoline imports, who grow monotonically with the retrofitting costs although the sales of European gasoline models grows much faster.

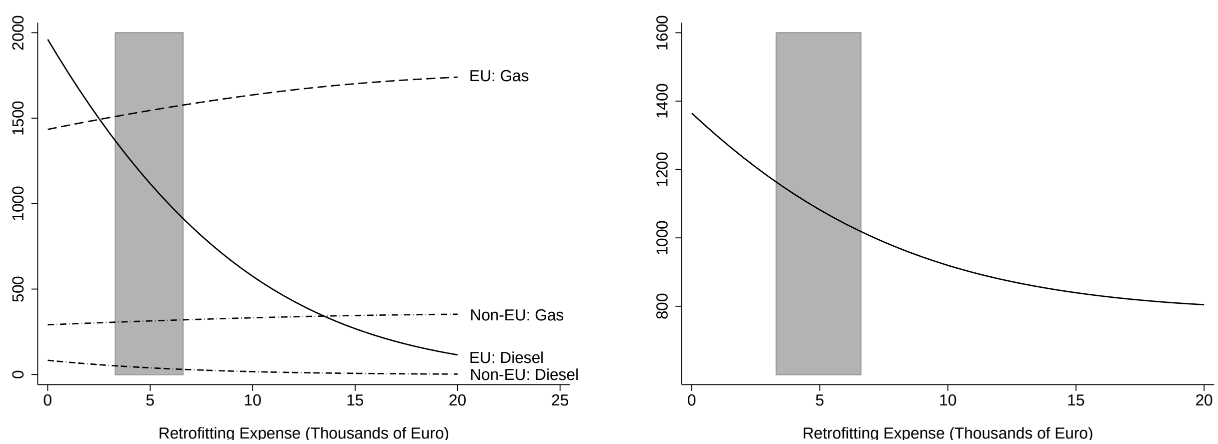
A detailed analysis of market shares of the different manufacturers reveals that the only clear beneficiaries of an alternative stringent European NO_x emission policy would be foreign automakers. As producers of inexpensive, fuel-efficient gasoline vehicles, the foreign auto makers benefit as consumers substitute away from the expensive diesel engines and towards gasoline. Although the composition of sales changes with retrofitting costs, most European manufacturers maintain a significant share of the market. That is not the case for the two European diesel leaders PSA and VOLKSWAGEN. Both of them are also the largest producers of diesel vehicles in Europe and thus, having to face these large retrofitting costs erode their competitiveness and their market shares. Lastly, it is important to note that the consumer's general preference for domestic automakers ($\beta_{NonEU} < 0$) limits their willingness to choose foreign imports. Had this home bias not existed, the shift from domestic to foreign cars would have been much larger.

6.2 Impact to Firms

The emphasis on market shares hides aggregate industry effects as more stringent emissions policy leads to higher retail prices and lower aggregate sales (Figure 9). The mechanism driving this decline is straightforward. While the model does allow for rich substitution patterns for consumers to switch to an alternative new car if the price of their first choice increases, the fact the alternative emissions policy increases the costs for a large number of cars simultaneously leads firms to increase price for both diesel and gasoline vehicles.

Consumers respond by leaving the market (panel b), presumably to purchase a used vehicle or to hold-off consumption altogether.[28] The results for firms, particularly European firms, are equally negative (panel a). VOLKSWAGEN and the PSA group, the heaviest adopters of diesels, are the biggest losers though most European firms experience a material reduction in profits. In comparison, Asian firms which had invested little in developing diesel products see their profits increase as consumers switch to their fuel-efficient gasoline models.

Figure 9: Impact of Alternative Emissions Policies on Firms



(a) Profit (€Millions)

(b) Quantity (000)

To quantify the aggregate impact of diesels, Table 4 reports the extreme case where an alternative emissions policy results in the elimination of diesels from the marketplace. For simplicity we just report results for year 2000 but other years yield similar results. While we admit this is a limiting case, it is worthwhile to remind the reader that this is indeed what happened in the United States market after CAAA implementation in the mid 1990s. Relative to the benchmark, the market shrinks considerably as consumers move to the outside good (*e.g.*, used car market). European automakers absorb the most of this impact as profits fall €2.2 billion, or 64 percent. Non-European, primarily Asian, auto makers, however, are better off as their market share jumps

[28] By holding the value of the outside option (*i.e.*, not buying a new car) fixed, we are assuming the average price and quality of a used car does not change with the regulation.

from 11.8% to 19.6% resulting in more market power and an increase retail prices, margins, and sales of their gasoline models following the disappearance of fuel-efficient diesel vehicles from the market. On net, profits for these firms increase €21 million, or 5.5 percent.

Table 4: Value of the Diesel

Scenario	Models	Price	Quantity	Margin	Share	Profit
Benchmark						
EU: DIESEL	75	16.19	695.37	18.68	50.95	1,961.00
EU: GASOLINE	84	14.93	508.70	21.09	37.28	1,434.37
NON-EU: DIESEL	20	17.20	36.97	14.84	2.71	83.26
NON-EU: GASOLINE	50	13.66	123.65	21.18	9.06	291.05
Equilibrium without Diesels						
EU: GASOLINE	84	21.11	412.58	16.95	80.40	1,236.29
NON-EU: GASOLINE	50	18.03	100.58	25.83	19.60	394.89

Results based on year 2000 equilibrium. "Price" is the sales-weighted average price faced by consumers (in thousands of 1994 Euros), including tariffs. "Quantity" is measured in millions of cars. "Profit" is measured in the equivalent of millions of 1994 Euro. "Margin" and "Share" are reported as percentages. "Margins" include import duties paid by consumers.

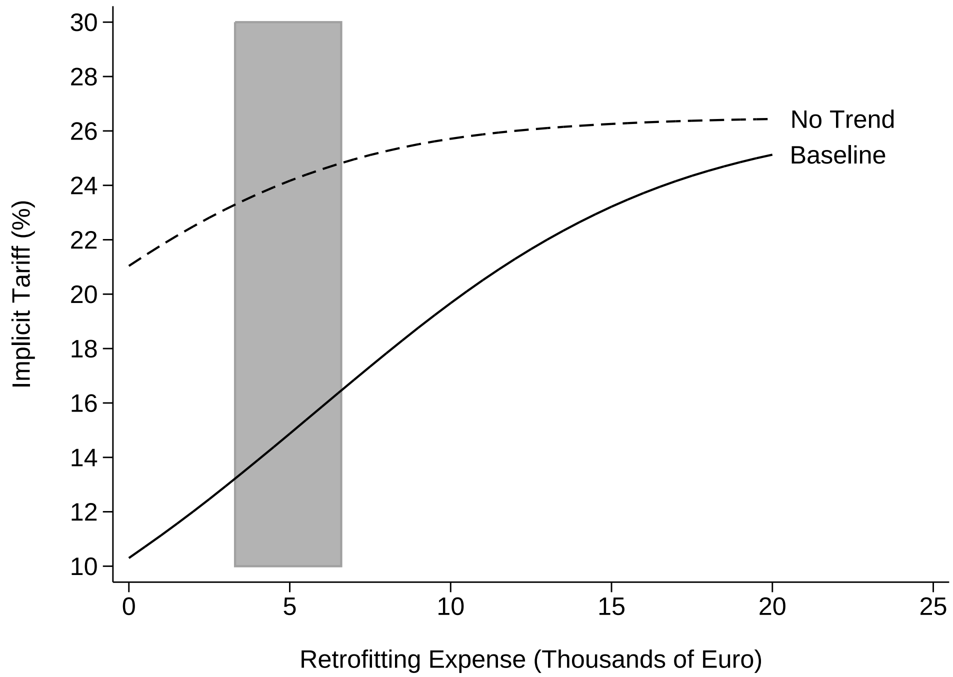
6.3 Import Tariff Equivalence of Environmental Regulation

We have so far shown that diesel vehicles were a popular choice among consumers; generating substantial profits for European auto makers. Reducing the popularity of these vehicles, presumably from an EPA-like emissions policy, would have resulted in a substantial reduction in profits for these firms while nearly doubling the market share of imports. In this section we use the structural model to measure the tariff-equivalence of European authorities' targeting of green house emissions. Whether this emission policy was designed explicitly to promote sales of domestically produced diesel vehicles is inconsequential. In practice, targeting CO_2 rather than NO_x generated precisely that result.

In Figure 10 we plot the import tariff required to generate the import share we observe (*e.g.*, 11.8% in 2000) for each level of retrofitting cost. We interpret each point as the import tariff-equivalence of the diesel-friendly emissions policy employed by EU regulators. For simplicity, we again restrict the current discussion to the year 2000 and show in Appendix F.1 (Table F.2) the results are similar for other years as well.

We find that the implicit tariff from by our "Baseline" estimation is significant, ranging from 13.4% when retrofitting costs are on the lower bound of the EPA estimates to 16.4% at the upper bound. For reference, the official import tariff facing Asian imports was 10.3% in 2000 so the diesel-friendly EU emissions policy amounted to 30-60 percent increase on the official rate, a significant effect. In the extreme case, a retrofitting cost which effectively eliminates the diesel

Figure 10: Import Tariff Equivalent of EU Emissions Policy



corresponds to a 26.5% import tariff. In other words, if the costs of modifying the diesel engine to meet stronger NO_x emissions standards are very large, the protective effect of adopting an emissions policy with a weak NO_x emissions standard is equivalent to imposing a tariff two-and-a-half times the official rate.

An advantage of our data set is that it covers a period of massive adoption of the diesel technology. In the estimation we allowed for consumer preferences towards diesels to change over the decade due to potentially learning or unobserved improvements in these vehicles. In the analysis thus far, we've held consumer preferences as fixed and only allowed substitution through changes in vehicle price due to retrofitting costs. We argue that the implementation of an alternative emissions policy early in the decade would not only affect immediate diesel sales through the changes in price but also future sales, particularly if one believes the increasing favorability of consumers is due to learning about the new technology. One would expect the EU's pro-diesel policy to increase the competitive advantage of diesels by buying time for consumers to learn about them. Conversely, an alternative emissions policy would limit consumer adoption due to increases in price, leave preferences towards diesels unchanged, and require a larger tariff to defend domestic auto makers.

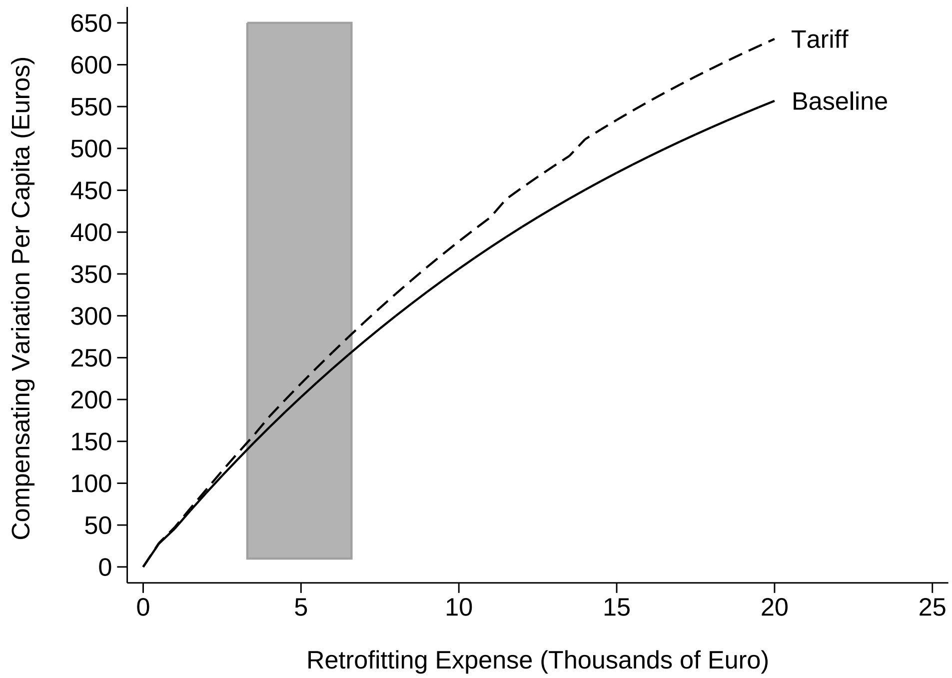
In Figure 10 we confirm this hypothesis by presenting results where we allow for the change in emissions policy to impact diesel demand through this second channel – *i.e.*, through consumer learning. We do this in the model by setting the diesel trend equal to zero ($\beta_{Diesel\ \times\ Trend} = 0$). The underlying assumption is that a positive estimate for the diesel trend in demand is due solely to increased consumer awareness of this next generation diesel technology. We then solve for the implicit tariff as in the "Baseline" experiment; finding implicit tariff increases from 13 to 24% at the lower bound of the EPA estimate and from 16 to 25% at the upper bound. Further, the "No Trend" curve is flatter suggesting that small retrofitting costs effectively eliminate the diesel segment. While we view this experiment as aggressive, it does reveal the quantitative importance of consumer learning in the evaluation of any policy that promotes diffusion of a new technology. For us, it also reveals that our "Baseline" estimates likely understate the trade implications.

Further refinement of the estimated implicit tariff depends crucially on pinning down a "realistic" retrofitting cost which is complicated since the reference EPA estimates are based on technology developed much later (2010) and one can imagine that European auto makers may have been able to develop a less expensive technology to protect their investment in diesels. The recent Volkswagen scandal suggests, however, that the costs of modifying these engines are indeed large since the company chose to incur severe financial penalties rather than meet the stricter EPA's NO_x thresholds. We take this as further evidence that a conservative estimate for the tariff-equivalent of observed EU emissions policy is between 13.4 and 16.4 percent, though we note that these values likely understates the actual effect provided one believes that the growth in diesels was due at least in part to consumer learning. Regardless, it is clear the emissions policy employed by European regulators favored domestic auto makers as a quantitatively significant *de facto* non-tariff trade policy during the 1990s.

6.4 Impact to Consumers

Thus far our analysis has focused on the impact of emissions regulation on firms in the automobile industry, particularly domestic and foreign firms. In this section we pivot to focus on consumers. In Figure 11 we show the amount of money required to compensate the average consumer in year 2000 under more rigorous emissions policies. The solid line indicates the average consumer requires €150-250 in compensation for the retrofitting costs within the range estimated by the EPA. The dashed line shows that consumers are further hurt (*i.e.*, require more compensation) when government imposes the "Baseline" import tariffs from Figure 10.

Figure 11: Impact of Alternative Emissions Policies on Consumers



While our welfare analysis does not account for the reduction in negative health externalities due to more rigorous NO_x standards, it does provide an interesting insight into non-tariff trade policies more broadly. Recall that so far we have shown that the emissions policy employed by EU regulators had the effect of promoting a domestic innovation. Further, we show in Figure 11 that this policy is unambiguously welfare improving if we assume health externalities are negligible. Putting these points together indicates that non-tariff trade policies which promote domestic innovations (or the adoption of products by domestic consumers) can not only be an effective tool to influence consumption towards domestic products but they may also improve consumer welfare. This stands in stark contrast with tariffs which influence consumption by distorting price, leading to less consumer surplus – a fact also illustrated in Figure 11.[29]

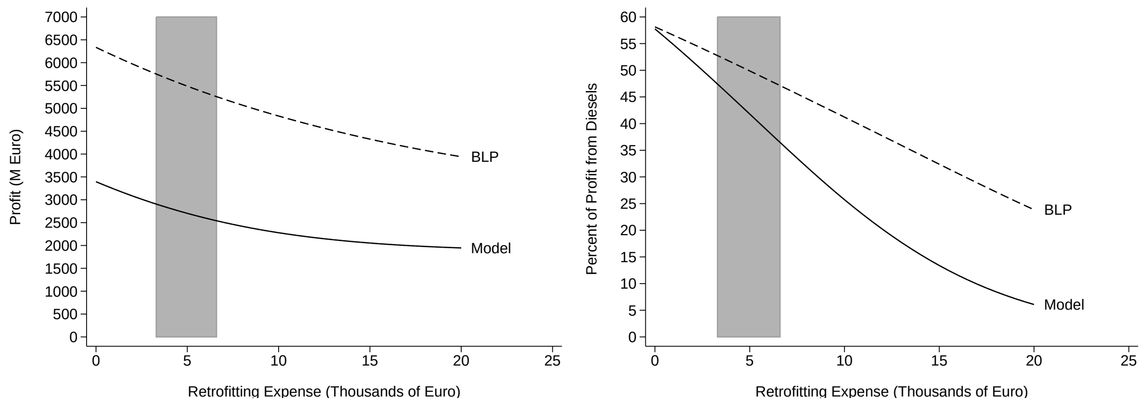
7 Robustness

In Section 5 we demonstrated that assuming product characteristic exogeneity led to steeper estimated demand curves and greater margins. The natural question is whether these differences materially impact our conclusions as to the effects of emissions policy on the European auto industry. In Figure 12 we compare the total profits of European firms (left panel) and the share of

[29] There is a large and growing empirical literature documenting the negative effects of tariffs on consumer welfare. See Ruhl (2008) for a review.

total profits contributed by diesels (right panel) as we vary the retrofitting costs across our baseline estimation ("Model") and the alternative *BLP* estimates ("BLP") from Table 2.

Figure 12: Value of Diesels by Estimation Approach



(a) Total Profits (b) Share of Profits from Diesels

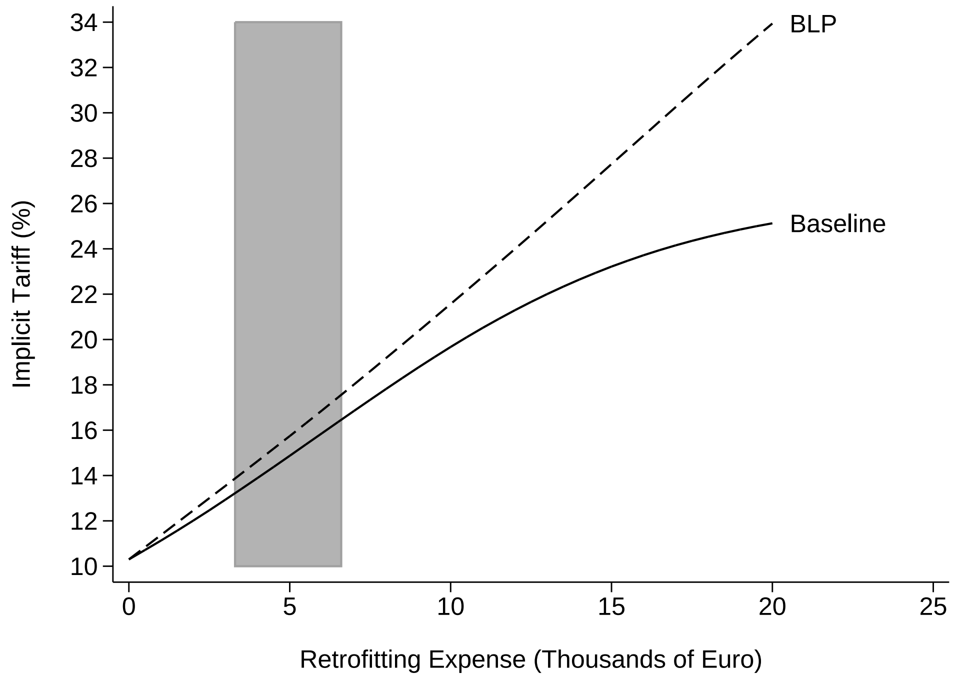
The steeper demand estimates from the *BLP* estimation leads to larger margins and greater profits for all products, not just diesels. We see this aggregate effect in a shifting up of the profit curves when moving from our baseline specification to the *BLP* estimates. The right panel illustrates that the shift is not uniform as diesels in our baseline model decrease in importance at a faster rate than in the *BLP* specification as the larger estimate for the diesel random coefficient in the latter specification makes consumers more willing to stay with the engine type despite increases in price. The lower estimated price elasticities in the *BLP* estimation also enables auto makers to pass-through increases in marginal cost to consumers leading to a more linear relationship between retrofitting costs and the importance of diesels, measured in total profits or in market share. We interpret these results as evidence that assuming product characteristic exogeneity biases the estimated value of diesel vehicles upwards, thereby overstating the effects of pro-diesel emissions policy on automakers and consumers alike.

Interestingly, this bias largely disappears, particularly for low estimates of the retrofitting costs, when we compare the implicit import tariffs from each demand estimation (Figure 13). Why does the estimation matter when analyzing the importance of diesels but not when we compare the implicit import tariff implied by these vehicles? The answer lies in the firms' first-order conditions for price:

$$p = [1+\tau] \times [\hat{\mathbf{mc}} + \underbrace{\Delta^{-1}(p, x, \hat{\xi}; \hat{\theta}) s_j(p, x, \hat{\xi}; \hat{\theta})}_{\textbf{markups}}], \tag{18}$$

The different estimation approaches impact our conclusions to the overall value of diesels through the markups via the estimated product elasticities, *e.g.*, see Panel (a) of Figure 12. Given

Figure 13: Implicit Import Tariff by Estimation Approach



that we observe price and use (18) to back-out marginal costs consistent with profit-maximization, the estimated price elasticities help the researcher split observed prices into marginal costs and markups. Therefore, under the *BLP* approach we find that consumers are less price-sensitive than under our baseline model which, in turn, leads us to allocate more of the observed prices to markups and greater profits for all cars, including diesels.

Recall that in Figure 13 we vary the import tariff τ to move the import share for each retrofitting cost back to the value observed in the data. Importantly, the import tariff τ increases marginal costs and markups proportionately so the relative size of the two matters less. Consequently, the net impact of using the simpler *BLP* approach depends on the complex substitution patterns embedded in the markup function, $\Delta^{-1}(p, x, \hat{\xi}; \hat{\theta})s_j(p, x, \hat{\xi}; \hat{\theta})$, which in this case appears to be small particularly in a neighborhood of the equilibrium observed in the data.

We use the above evidence to form two conclusions. The first is cautionary as Figure 12 clearly shows that a researcher who uses a discrete choice model to estimate markups (*e.g.*, quantifying the value of a good) should be wary of estimates based on product exogeneity as such an assumption will significantly bias her results upwards. The second is more optimistic as researchers interested in economic mechanisms in which the estimated markups are not of themselves important may be able to use the much simpler *BLP* approach to generate reasonable results. Proving this distinction more formally is an interesting and, given the prevalence of *BLP*-type models, potentially important area of future research.

8 Concluding Remarks

The goal in this paper was to evaluate the role of vehicle emissions policy in the growth of the diesel segment in the European automobile industry. To do so we estimated a structural oligopoly model of differentiated products where we allowed for correlation between observed and unobserved product characteristics, finding the two are indeed correlated. Our estimation allowed for significant heterogeneity of preferences, finding that consumers not only favor fuel efficiency and car size but also that their perception of diesels improved dramatically in the decade following the introduction of these next generation engines. We also find that widespread imitation of the TDI by European auto makers due to the generality of the technology enabled domestic firms to generate substantial profits from the technology.

Perhaps the most novel result of our paper is to show that seemingly non-trade policies such as environmental standards can have important and quantitatively significant trade effects. Regardless of whether the European pro-greenhouse emission policy was intended to favor the sales of domestically produced diesel vehicles or not, we show that alternative NO_x reduction policies would have effectively halted the commercial success of diesel vehicles. Further, the diesel-friendly emissions policy favored domestic firms equivalent to an implicit import tariff ranging from 13.4% to 16.4%, or approximately a 30 to 60% increase over the official tariff employed by the European Union at the time. Moreover, we show this result is robust across a variety of assumptions, including the estimation approach. This is, to the best of our knowledge, the first use of a structural equilibrium model of demand and industry oligopoly competition to evaluate the trade effects of a non-tariff policy. Our results illustrate that in an increasingly global economy, governments can effectively construct non-trade oriented national policies, including environmental regulations, to protect domestic industries when traditional trade policies are no longer available. We further show that, in contrast to tariffs, such a policy may be welfare improving.

While our modeling choices are sufficient to address the objectives in this paper – balancing a feasible extension of the *BLP* framework while meeting the institutional details of our application – we view this paper as a step towards developing a more realistic empirical model of the automobile industry by providing useful insights into the quantitative implications of attribute choices made by firms.[30]

[30] Crawford (2012) presents a recent overview of the challenges of fully addressing the endogeneity of product attributes in discrete choice models of demand.

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Appendix

A Spanish Data Sources

To control for household income distribution a thousand individuals are sampled each year from the *Encuesta Continua de Presupuestos Familiares* (Base 1987 for years 1992-1997 and Base 1997 for years 1998-2000) conducted by INE, the Spanish Statistical Agency.[31] The outside option varies significantly during the 1990s due to the important recession between 1992 and 1994 and the very fast growth of the economy and population (immigration) in the second half of the decade. We also use these consumer surveys to set the size of the outside option for each year in our sample. Starting with 1992, they are: 0.92, 0.94, 0.93, 0.93, 0.93, 0.92, 0.91, 0.89, and 0.89, respectively.

Fuel prices were also obtained from INE. In real 1994 euro-equivalent denominations per liter, these are 0.445, 0.488, 0.490, 0.493, 0.543, 0.560. 0.530, 0.565, and 0.695 for diesel and 0.580, 0.628, 0.655, 0.678, 0.706, 0.724, 0.702, 0.737, and 0.875 for gasoline, for years 1992 to 2000, respectively. As for the Spanish steel prices used as instruments for the cost equations, they are obtained from the 2001 edition of *Iron and Steel Statistics – Data 1991-2000* published by the European Commission (Table 8.1).

For the analysis of demand we build a data set using prices and vehicle characteristics as reported by *La guía del comprador de coches*, ed. Moredi, Madrid. We select the price and characteristics of the mid-range version of each model, *i.e.*, the most popular and commonly sold. Demand estimation also makes use of segment dummies. Other than the LUXURY segment, which also includes sporty cars, our car segments follow the "Euro Car Segment" definition described in Section IV of "Case No. COMP/M.1406 - Hyundai/Kia." *Regulation (EEC) No. 4064/89: Merger Procedure Article 6(1)(b) Decision.* Brussels, 17 March 1999. CELEX Database Document No. 399M1406.

Until Spain ended its accession to the European Union transition period in 1992, it was allowed to charge import duties on European products. Similarly, import duties for non-European products converged to European levels. European imports paid tax duty of 4.4% in 1992, and nothing thereafter. Non-European manufacturers had to pay 14.4% and 10.3%, respectively. Thus, for the estimation of the equilibrium random coefficient discrete choice model of Table 2 we distinguish between prices paid by consumers (p) and those chosen by manufacturers (p^{τ}) .

The other relevant factor that changes during the 1990s is the ownership structure of automobile firms. During this decade FIAT acquired ALFA ROMEO and LANCIA; FORD acquired VOLVO; and GM acquired SAAB. BMW acquired ROVER in 1994 but sold it in May 2000 (with the exception of the "Mini" brand) so these are treated as separate firms. Table A.1 describes the ownership structure at the beginning and end of the decade.

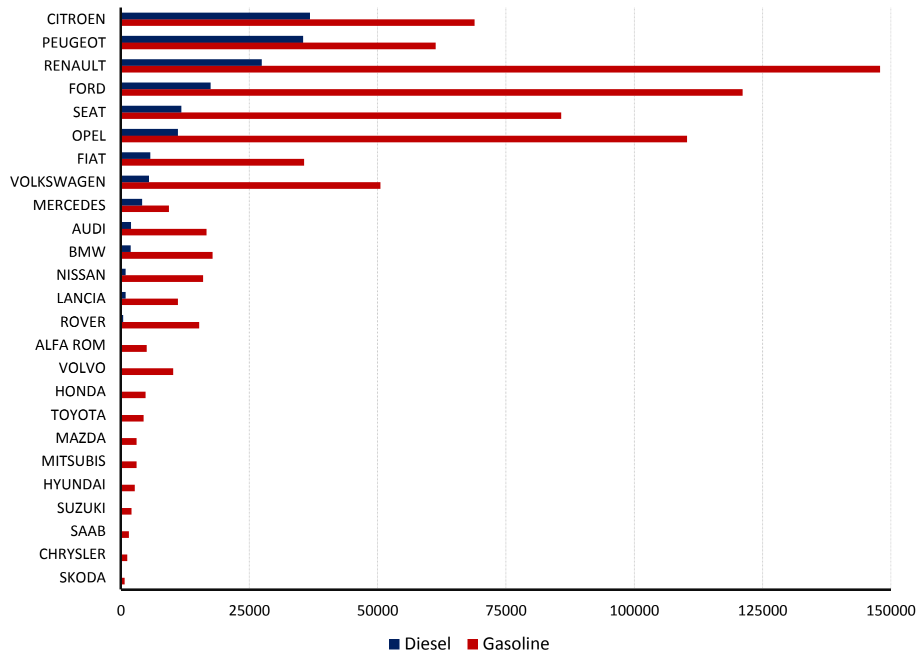
[31] See `http://www.ine.es/jaxi/menu.do?L=1&type=pcaxis&path=/t25/p458&file=inebase` for a description of these databases in English.

Table A.1: Automobile Groups: 1992 vs. 2000

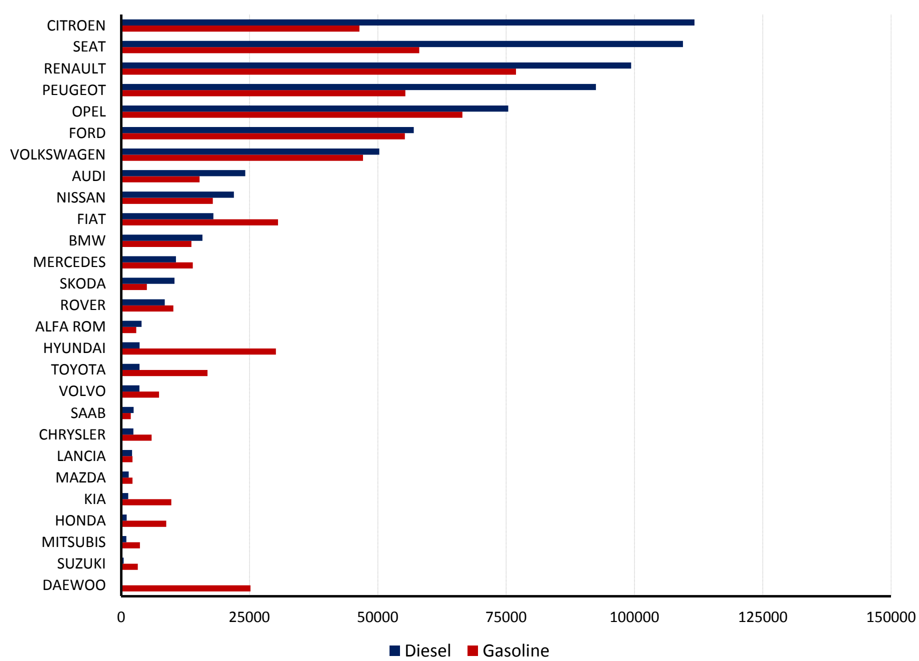
	Year 1992			Year 2000		
Firm	Gasoline	Diesel	Owner	Gasoline	Diesel	Owner
ALFA ROMEO	5,038	64	ALFA ROMEO	2,941	3,983	FIAT
AUDI	16,689	1,982	VOLKSWAGEN	15,273	24,184	VOLKSWAGEN
BMW	17,855	1,906	BMW	13,683	15,838	BMW
CHRYSLER	1,243	–		5,941	2,389	
CITROËN	68,890	36,851	PSA	46,420	111,694	PSA
DAEWOO	–	–		25,201	–	
FIAT	35,677	5,733	FIAT	30,557	17,967	FIAT
FORD	121,140	17,468	FORD	55,268	57,013	FORD
HONDA	4,805	–		8,782	1,072	
HYUNDAI	2,704	–		30,150	3,590	
KIA	–	–		9,778	1,387	
LANCIA	11,117	905	LANCIA	2,206	2,126	FIAT
MAZDA	3,064	–		2,205	1,480	
MERCEDES	9,352	4,129	MERCEDES	13,953	10,684	MERCEDES
MITSUBISHI	3,041	–		3,660	1,013	
NISSAN	16,010	905		17,855	21,971	
OPEL	110,286	11,099	GM	66,488	75,418	GM
PEUGEOT	61,323	35,494	PSA	55,371	92,496	PSA
RENAULT	147,907	27,448	RENAULT	76,925	99,360	RENAULT
ROVER	15,255	425	ROVER	10,173	8,491	ROVER
SAAB	1,551	–	SAAB	1,867	2,424	GM
SEAT	85,773	11,787	VOLKSWAGEN	58,072	109,447	VOLKSWAGEN
SKODA	724	–	SKODA	5,003	10,385	VOLKSWAGEN
SUZUKI	2,058	–		3,250	486	
TOYOTA	4,425	–		16,827	3,584	
VOLKSWAGEN	50,561	5,471	VOLKSWAGEN	47,125	50,296	VOLKSWAGEN
VOLVO	10,179	–	VOLVO	7,379	3,566	FORD

Sales of vehicle by manufacturer and fuel type. "Owner" indicates the name of the automobile group with direct control on production and pricing. Those without a group are all non-European manufacturers and defined as NON-EU in the analysis.

Figure A.1: Sales by Firm and Type of Engine



(a) Year 1992



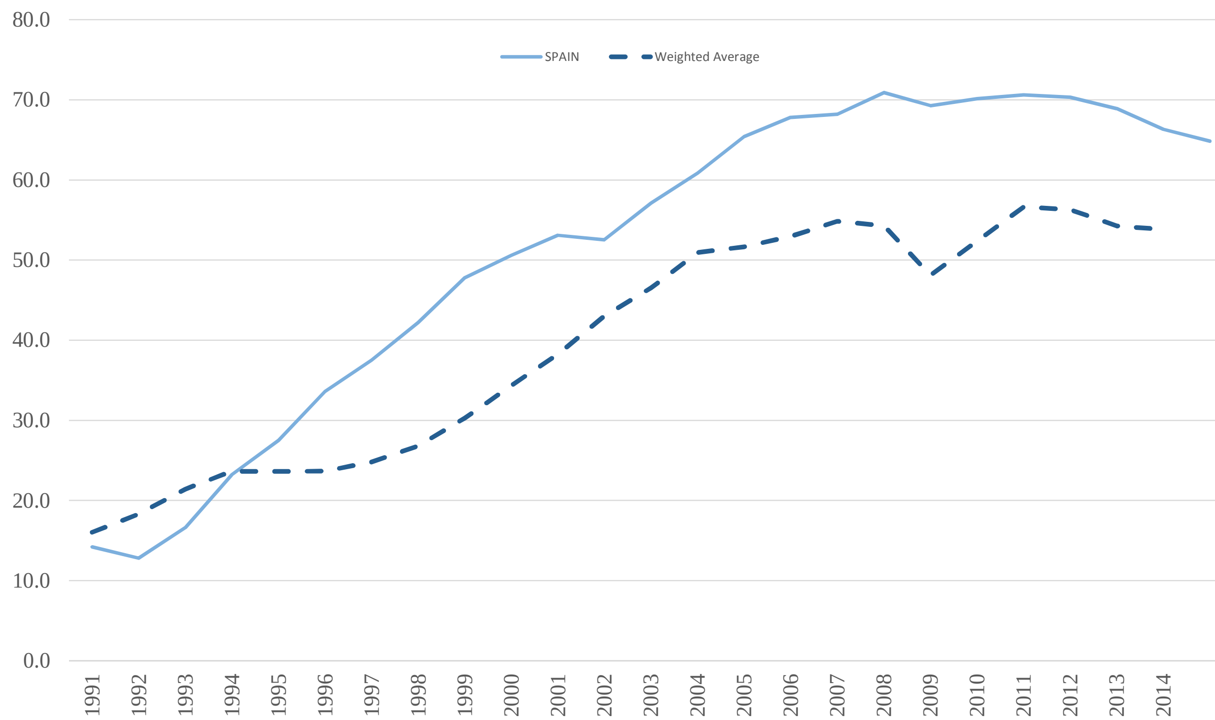
(b) Year 2000

Table A.2: Car Model Characteristics Across Engine Types

SEGMENT	MODELS	SHARE	PRICE	C90	KPE	SIZE	HPW
1992							
Compact	31	35.79	10.96	5.33	32.07	74.34	3.98
Sedan	39	22.31	14.26	5.69	30.27	80.10	4.26
Luxury	39	5.77	24.01	6.49	25.75	87.07	4.84
Minivan	4	0.32	17.28	6.93	24.21	81.66	3.79
Small	28	35.82	7.98	4.68	35.00	62.51	3.65
All	141	100.00	11.40	5.25	32.33	72.15	3.97
2000							
Compact	56	34.43	14.86	5.00	32.53	76.54	3.59
Sedan	52	25.97	19.45	5.26	31.60	81.92	3.63
Luxury	40	3.72	34.53	6.72	23.31	89.72	5.17
Minivan	32	3.13	20.80	6.39	25.91	83.47	3.16
Small	49	32.75	10.42	4.86	31.61	66.36	3.18
All	229	100.00	15.52	5.13	31.43	75.31	3.51

Notes: SHARE is the market share as defined by automobiles sold. PRICE is denominated in the equivalent of thousands of 1994 Euros and includes value added taxes and import tariffs. KPE is the distance, measured in kilometers, traveled per euro of fuel. SIZE is length×width measured in square feet. HPW is the performance ratio of horsepower per hundred pounds of weight.

Figure A.2: Diesel Adoption Rates



Notes: Authors' calculations. New passenger car registration data from *Association Auxiliaire de l'Automobile (AAA)*. European diesel penetration (dashed line) constructed gross domestic product as weights (source: World Bank Development Indicators). Countries included: Austria, Belgium, Denmark, France, Germany, Ireland, Italy, Luxembourg, Netherlands, Portugal, and the United Kingdom.

B Estimation: Solving the Model

In this section we describe our algorithm to solve the model conditional on parameter guess $\theta = [\beta, \Sigma, \Pi, \gamma]$. Since solving the model is independent across years, we drop the t subscripts for brevity. The algorithm is as follows:

1. Compute δ using the contraction mapping described in (Berry et al., 1995, Appendix I).
2. Use $\mu(\Sigma, \Pi)$ and $s_{ijt}(\theta)$ to solve for the implied markups b_j. Use the firms' first-order conditions for the pricing game (Equation 7) and the observed prices to construct marginal costs (c).
3. Use δ from (1) and the β parameter vector guess to solve for ξ.
4. Use the marginal costs (c) from (2) and the γ parameter vector guess to solve for ω.
5. Use the assumed information structure Ψ to construct the structural error ν_j^k:

$$\nu_j^k(\theta;\Psi) = s_j(\theta;\Psi) \times \frac{\partial(p_j^\tau(\theta;\Psi) - c_j(\theta;\Psi))}{\partial x_j^k} + \sum_{r \in \mathcal{F}_f} (p_r^\tau(\theta;\Psi) - c_r(\theta;\Psi)) \times \frac{\partial s_r(\theta;\Psi)}{\partial x_j^k}. \quad \text{(B.1)}$$

   using the following algorithm:

   (a) Use $\hat{\gamma}$ and the Cobb-Douglas specification of the marginal cost equation to generate $\frac{\partial c_j}{\partial X_j^k}$.

   (b) Evaluate the indirect (price-induced) market share response to attributes from:

$$\frac{\partial s_r}{\partial x_j^k} = \begin{cases} \int_{\nu^k}\int_D (\beta^k + \sigma^k \nu^k + \pi^k D) \times s_{ij}(1 - s_{ir}) dP_D(D) dP_\nu(\nu) + \sum_{m \in \mathcal{F}_f} \frac{\partial s_r}{\partial p_m}\frac{\partial p_m}{\partial x_j^k}, & r = j, \\ -\int_{\nu^k}\int_D (\beta^k + \sigma^k \nu^k + \pi^k D) \times s_{ij} s_{ir} dP_D(D) dP_\nu(\nu) + \sum_{m \in \mathcal{F}_f} \frac{\partial s_r}{\partial p_m}\frac{\partial p_m}{\partial x_j^k}, & \text{otherwise}. \end{cases} \quad \text{(B.2)}$$

   where we solve for $\frac{p_m^\tau}{\partial x_j^k}$ using the market shares and implicit function theorem. Note that the dependence upon Ψ in Equation B.2 is assumed (and therefore dropped from the notation for brevity). Equation B.2 requires solving for a fixed point in the matrix $\frac{\partial s}{\partial x}$. While we have no proof that our operator is a contraction or that it results in a unique solution, we found that updating guesses using a convex combination of the previous and new guess yielded fast, monotonic convergence and that starting from different initial guesses yielded the same results.

   (c) Since we allow for $\Psi = \Psi_t^f$ to vary by firm (*i.e.*, firms may have different beliefs about the future), we solve for the structural errors (ν) firm-by-firm.

C EPA Cost Estimates for Retrofitting Diesel Vehicles

The following information was taken from *'Diesel Retrofit Devices."* Environmental Protection Agency (`http://www.epa.gov/cleandiesel/technologies/retrofits.htm`), last updated January 23, 2013. As described in the text, the retrofitting technology we consider is the "Lean NOx Catalyst (LNC)" as this technology is most relevant for limiting NOx emissions in passenger cars. Our inclusion of the remaining technologies recommended by the EPA shows both the breadth of technologies available to reduce a variety of emissions as well as the variety of costs (of which the LNC is near the bottom) required to retrofit a vehicle.

> Diesel retrofit devices for after-treatment pollution control can be installed on new or existing vehicles and equipment to reduce particulate matter (PM), nitrogen oxides (NOx), hydrocarbons (HC), or carbon monoxide (CO) as well as other air pollutants. The information below provides estimated emission reductions.

Table C.1: Estimated Costs to Retrofit Diesel Vehicles

Technology	Typical NO_x Emission Reduction	Typical Cost ($)
Lean NOx Catalyst (LNC)	5-40%	$6,500-$10,000
Selective Catalytic Reduction (SCR)	$<$75%	$10,000-$20,000; Urea $0.80/ gallon

Source: United States Environmental Protection Agency.

> Lean NOx Catalyst (LNC) Lean NOx Catalysts (LNC) use diesel fuel injected into the exhaust stream to create a catalytic reaction and reduce pollution. Verified LNCs are paired with either a DPF or a DOC. An LNC can also be paired with an active DPF to reduce NOx emissions and enable filter regeneration over a range of duty cycles. However, an LNC still requires specific exhaust temperatures for appropriate NOx emission control performance. *LNCs can increase fuel usage by 5-7 percent* (emphasis added).

> Selective Catalytic Reduction (SCR) Selective Catalytic Reduction (SCR) Systems inject a reductant, also known as diesel exhaust fluid (DEF), into the exhaust stream where it reacts with a catalyst to convert NOx emissions to N2 (nitrogen gas) and oxygen. The catalytic reaction requires certain temperature criteria for NOx reduction to occur. As with DPFs, knowing the age and type of each engine in the fleet as well as the drive cycles of the vehicles is important. Data logging must be performed to determine if the exhaust gas temperatures meet the specific SCR system requirements.
>
> SCR systems require periodic refilling of the DEF, and the system should ensure that the DEF never freezes. SCR systems are commonly used in conjunction with a DOC and/or DPF to reduce PM emissions. Because of new NOx standards, most 2010 and

newer on-highway diesel engines come equipped with an SCR system. A DEF refueling infrastructure is in place, facilitating the use of SCRs.

D Solving for Counterfactual Automobile Prices

In this section we provide computational details to find the profit-maximizing prices under each policy experiment. For the sake of brevity, we suppress the period subscripts. Each firm f produces some subset $\mathcal{F}_f$ of the $j = 1, \ldots, J$ automobile brands and chooses a vector of pre-tariff prices $\{p_j^\tau\}$ to solve:

$$\max_{\{p_j^\tau\}} \sum_{j\in\mathcal{F}_f} \left(p_j^\tau - c_j\right) \times Ms_j \,, \tag{D.1}$$

The firm's first-order condition for price conditional on product characteristics is given by:

$$s_j + \sum_{r\in\mathcal{F}_f} (p_r^\tau - c_r) \times \frac{\partial s_r}{\partial p_j^\tau} = 0 \,. \tag{D.2}$$

Optimality requires that Equation (D.2) hold for all products sold in period t. We express the set of firm f first-order conditions in matrix notation as:

$$s + \Delta \times (p^\tau - c) = 0 \,, \tag{D.3}$$

where an element of the matrix Ω is defined as:

$$\Omega_{jr} = \begin{cases} \dfrac{\partial s_j}{\partial p_r^\tau} \,, & \text{if } \{j, r\} \ \subset \mathcal{F}_f \,, \\ \\ 0 & \text{otherwise} \,. \end{cases} \tag{D.4}$$

For a given vector of marginal costs c, we use (D.3) to find the fixed point to the system of equations – a common practice in the literature dealing with this class of models. To our knowledge there exists no proof of convergence or uniqueness for this contraction operator and fixed point. Our experience (as is common) is that convergence is monotonic and proceeds quickly. Further, starting from different starting values yields an identical result.

E Fuel Taxation as a Policy Tool to Promote Diesels

Following the European Fuel Taxation Directive of the 1970s, diesel fuel received a favorable treatment that has convinced many to conclude that the success of diesel vehicles in Europe was due primarily to this favorable treatment of diesel fuel taxation. We argued in Section 2.2 that the reduced diesel fuel tax rate was instrumental for the development of a diesel market niche that eased the adoption of TDI (and likely influenced its development) and other improved diesel vehicles in the 1990s, two decades after the European Fuel Tax Directive was adopted. Given this initial condition, it is unclear to what degree preferential fuel taxes influenced the domestic market versus the diesel-friendly environmental emissions policy. Moreover, both policies have the potential to protect domestic industry by promoting its competitive advantage among consumers. The goal of this appendix is to quantify the impacts of each to assess the relative impact on the industry.

In our first experiment (third panel of Table E.1) we replace the European fuel taxes with average values employed in the United States where taxes are not only lower but also favor gasoline.[32] The reduction in fuel price increases their fuel efficiency, KPE, and consequently the attractiveness of new cars (since $\sigma_{\text{KPE}} > 0$), increasing total consumption 10.6 percent, though the increase is across both gasoline and diesel. The increase in diesel is more muted (3.7%) than gasoline (18.7%) and both European firms and Non-European firms experience significant increases in profits (9.7% and 11.6%, respectively). Conversely, quantity sold for diesels in our estimated equilibrium (first panel) are 3.5% lower than under U.S. fuel taxes and both European firms and Non-European firms experience are worse off under the current tax policy (8.8% and 10.4%, respectively).

In the fourth and fifth panels we evaluate the consequences of equalizing fuel taxes and increasing fuel taxes by 8.1% in line with current policy.[33] When we increase fuel taxes to the level applied to gasoline, the higher fuel prices and lower fuel economy lead consumers to substitute towards gasoline. Consequently, diesel sales and profits in the estimated equilibrium are 5.4% and 5.4% greater in the estimated equilibrium. We see similar results in the current EU fuel taxation policy where higher diesel fuel taxes lead consumers to substitute away from diesel varieties indicating that the policy employed in the 1990s did the opposite – it encouraged consumers to purchase the diesel cars largely produced by domestic auto makers.

We compare these results to the market equilibrium when auto makers are required to meet stricter emissions requirements on NO_x emissions (panel 2). Here, we use the lower-bound on the EPA retrofitting cost as a conservative estimate. While pro-diesel fuel taxes increased consumption of diesels around six percent, the pro-diesel emissions policy employed by the EU increased total sales of diesels by 61.1% and most of these gains were captured by European automakers – profits for EU automakers in our estimated equilibrium increased €610 million (21.9%). Total profits for non-European auto makers also increases since some of these firms had adopted diesels though the results are meager compared to their European rivals. These results indicate that while preferential fuel taxes did play a role in promoting diesels and protecting domestic auto makers, fuel taxes play a minor role compared to the diesel-friendly emissions policy employed by EU regulators.

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[32] In constructing these average tax rates we computed the average fuel taxes across states, weighting by aggregate state fuel usage.

[33] Finally, after almost two decades of deliberation and negotiation among European policy makers, the European Fuel Tax Directive of the 1970s was updated to account for the energy content of each type of fuel (instead of just its volume) as well as for their disparate environmental impact. These new taxation principles were supposed to eliminate the favorable taxation of diesel fuels among others. Excise fuel taxes at the bottom panel of Table E.1 are those in place during 2015 according to E.U. Technical Press Briefing available at `http://ec.europa.eu/taxation_customs/resources/documents/taxation/review_of_regulation_en.pdf`

Table E.1: Modifying Diesel Fuel Taxes

Benchmark Diesel and Gas Excise Taxes

	Fuel Tax	Price	Quantity	Margin	Share	Profit
EU: DIESEL	0.23	16.19	695.37	18.68	50.95	1,961.00
EU: GASOLINE	0.35	14.93	508.70	21.09	37.28	1,434.37
NON-EU: DIESEL	0.23	17.20	36.97	14.84	2.71	83.26
NON-EU: GASOLINE	0.35	13.66	123.65	21.18	9.06	291.05
TOTAL	0.29	15.52	1,364.70	19.70	100.00	3,769.68

Retrofitting Expense of $3,600 Euros

	Fuel Tax	Price	Quantity	Margin	Share	Profit
EU: DIESEL	0.23	20.02	462.89	15.12	40.15	1,336.27
EU: GASOLINE	0.35	14.90	537.88	21.08	46.66	1,514.13
NON-EU: DIESEL	0.23	21.24	21.40	12.23	1.86	49.52
NON-EU: GASOLINE	0.35	13.65	130.64	21.18	11.33	307.27
TOTAL	0.30	16.93	1,152.81	18.53	100.00	3,207.18

US Fuel Taxes

	Fuel Tax	Price	Quantity	Margin	Share	Profit
EU: DIESEL	0.15	16.11	721.96	18.73	47.82	2,033.11
EU: GASOLINE	0.14	14.52	606.24	21.31	40.16	1,691.01
NON-EU: DIESEL	0.15	17.14	37.16	14.84	2.46	83.47
NON-EU: GASOLINE	0.14	13.29	144.35	21.35	9.56	334.35
TOTAL	0.14	15.23	1,509.71	19.92	100.00	4,141.95

Diesel and Gas Excise Taxes are the Same

	Fuel Tax	Price	Quantity	Margin	Share	Profit
EU: DIESEL	0.35	16.24	658.35	18.62	49.34	1,855.48
EU: GASOLINE	0.35	14.92	514.78	21.10	38.58	1,451.84
NON-EU: DIESEL	0.35	17.25	36.20	14.82	2.71	81.63
NON-EU: GASOLINE	0.35	13.66	125.02	21.19	9.37	294.38
TOTAL	0.35	15.52	1,334.34	19.71	100.00	3,683.32

Diesel Excise Tax is Increased

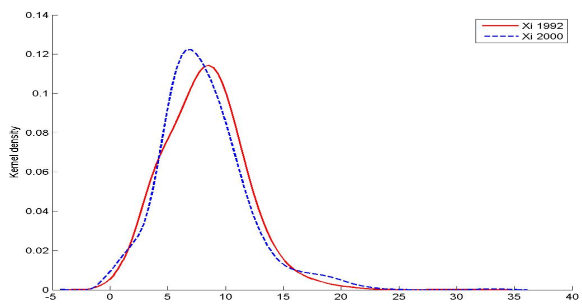
	Fuel Tax	Price	Quantity	Margin	Share	Profit
EU: DIESEL	0.38	16.25	651.51	18.61	49.03	1,835.82
EU: GASOLINE	0.35	14.92	515.92	21.10	38.83	1,455.11
NON-EU: DIESEL	0.38	17.26	36.04	14.82	2.71	81.30
NON-EU: GASOLINE	0.35	13.66	125.27	21.19	9.43	295.00
TOTAL	0.37	15.52	1,328.74	19.72	100.00	3,667.22

Notes: Results based on year 2000 equilibrium. "Fuel Tax" is measured in 1994 Euros per liter and TOTAL is the sales-weighted average fuel excise tax. "Price" is the sales-weighted average price faced by consumers (in thousands of 1994 Euros), including tariffs. "Quantity" is measured in thousands of cars. "Profit" is measured in millions of 1994 Euro. "Margin" and "Share" are reported as percentages.

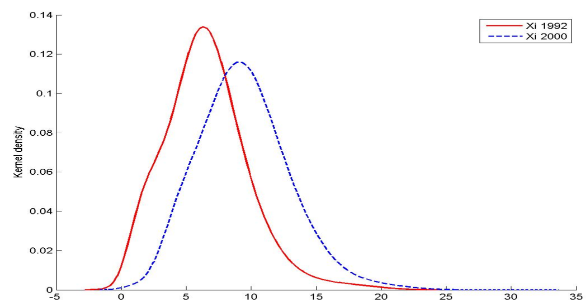
F Additional Results

F.1 *Unobserved Characteristics* In Figure F.1 we present the evolution of estimated unobservable quality $\hat{\xi}$ by year and fuel type. Table F.1 reports tests of stochastic dominance for these distributions. It is remarkable that while the unobservable attributes of gasoline vehicles are indistinguishable at the beginning and end of the 1990s, the perceived quality of diesels clearly improved during that same time period. Consumers were uncertain about unobservable features such as durability, torque, or reliability at the introduction of TDI. We also find that not only diesels (or consumers' perception of diesels) improve during the 1990s but that they are also linked to power, size, brand, and other observable automobile attributes.

Figure F.1: Change in the Distribution of Unobserved Attributes



(a) Gasoline: $\hat{\xi}$



(b) Diesel: $\hat{\xi}$

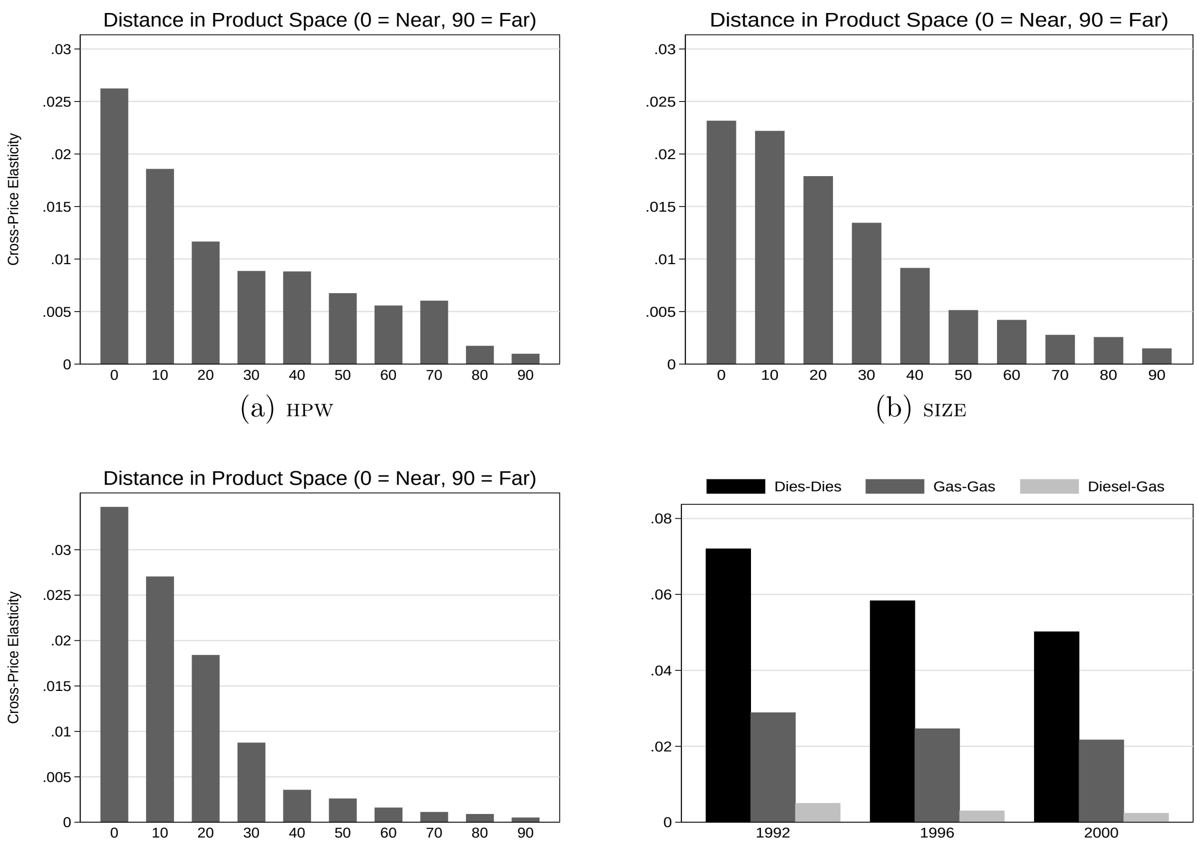
Table F.1: Distribution of Attributes

	2000 *vs* 1992		1992 *vs* 2000	
	SD1	SD2	SD1	SD2
GASOLINE				
C90	0.202	0.207	0.723	0.509
KPE	0.000	0.000	1.000	0.789
SIZE	0.697	0.825	0.454	0.273
HPW	1.000	0.830	0.024	0.003
$\hat{\xi}$	0.798	0.532	0.202	0.174
DIESEL				
C90	0.845	0.670	0.000	0.000
KPE	0.000	0.000	1.000	0.780
SIZE	1.000	0.865	0.000	0.000
HPW	0.002	0.123	0.000	0.000
$\hat{\xi}$	1.000	0.736	0.000	0.000

Kolmogorov-Smirnov tests of first (SD1) and second (SD2) order stochastic dominance where reported p-values are based on the consistent inference of Barrett and Donald (2003) using 1000 replications and 100 grid points on two random samples, for 1992 and 2000, of a thousand draws from the kernel distribution densities of each attribute. A p-value smaller than 0.05 *rejects* the null stochastic dominance hypothesis.

F.2 <u>*Substitution Patterns*</u> In Figure F.2 we present evidence that our model generates reasonable substitution patterns. We show this by first solving for the distance between each pair of products in a particular characteristic (*e.g.*, HPW). We then divide the product-pairs into deciles where the first decile correspond to pairs which are most alike. Finally, we compute the average cross-price elasticity for each bin. The results are plotted in panels (a-c) where we see clearly that for all of the characteristics considered in our estimation, substitution between similar products is much more likely than for products far apart in characteristic space. Since diesel is a discrete variable, we show the average cross-price elasticity within and across fuel types (panel d). Again, we see that consumers are much more likely to substitute within fuel type

Figure F.2: Cross-Price Elasticities



(a) HPW

(b) SIZE

(c) KPE

(d) FUEL TYPE

F.3 *Robustness* In Table F.2 we show that although the analysis focused on the year 2000, our conclusions extend across the 1990s.

Table F.2: Implicit Tariff by Year and Estimation Approach

	Import	Baseline		No Trend		BLP	
Year	Tariff	LB	UB	LB	UB	LB	UB
1992	14.40	16.29	17.23	16.29	17.23	16.84	18.48
1993	10.30	12.67	13.81	13.22	14.15	13.35	15.46
1994	10.30	12.55	13.83	13.69	14.60	12.95	14.93
1995	10.30	12.92	14.64	15.05	16.04	13.73	16.37
1996	10.30	12.78	14.54	15.76	16.83	13.67	16.08
1997	10.30	12.74	14.63	16.56	17.53	13.12	15.50
1998	10.30	12.97	15.27	18.73	19.87	13.43	16.04
1999	10.30	13.58	16.52	21.82	23.40	14.22	17.62
2000	10.30	13.41	16.36	23.41	24.78	14.09	17.44

Notes: "Import Tariff" is the official import tariff placed on foreign imports. Lower bound ("LB") and upper bound ("UB") retrofitting estimates based on installing a Lean NOx Catalyst (LNC). Technical and cost details located in Appendix C.